Factors influencing the performance of innovation contests

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Factors Influencing the Performance of Innovation Contests

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Contents

1 Introduction

1.1 The Rise of Innovation Contests

Over the past few years there has been a rapid surge of firms proactively integrating external input into their endeavors of developing new products and services (Adamczyk, Bullinger, & Möslein, 2012; Bockstedt, Druehl, & Mishra, 2015). Customers and other individuals who are not employed by the focal firm, who were insulated from innovation activities in the past, and passively responded to the innovation outcomes before, are more proactively involved in the innovation process. Scholars use the concept of "open innovation" to capture such innovation activities. Open innovation can be defined as "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization's business model" (Chesbrough & Bogers, 2014). Open innovation assumes that corporate innovation processes are more like an open system than the traditional vertically integrated model (West, Salter, Vanhaverbeke, & Chesbrough, 2014). Three factors contribute to the popularity of open innovation(West et al., 2014). First, innovation scholars have already realized that creative ideas are often developed externally. Second, open innovation does not harm to firms capturing returns from their innovation effort. And third, the Internet has been leveraged by firms to develop new business models and to promote the innovation activities. Depending on the purpose firms have and/or the characteristics of the innovation project, four main approaches to open innovation can be chosen: collaborative communities, complementors, labor markets, and contests (Boudreau & Lakhani, 2013).

Collaborative communities are usually organized by firms to marshal the outputs of multiple contributors and to integrate them into a coherent and value-creating whole (Bayus, 2013; Boudreau & Lakhani, 2013). An example of collaborative communities is the IdeaStorm Community[1] hosted by DELL. The second type of crowd-powered innovation is complementors. It usually consists of a core product or technology developed or maintained by a firm, and various complementary innovations developed by individuals based on the core product or technology. An example of complementors is

[1] www.ideastorm.com

iTunes[2], the mobile Apps platform hosted by Apple. The third approach to crowd-powered innovation is labor markets. Labor markets are flexible platforms serving as spot markets, matching skilled workers to specific tasks. An example of labor markets is clickworker[3].

The last one, which is also the research object of this dissertation, concerns innovation contests. Innovation contests can be generally defined as IT-based and time-limited competitions arranged by an organization or individual calling on the general public or a specific target group to make use of their expertise, skills or creativity in order to submit a solution for a particular task previously defined by the organizer who strives for an innovative solution (Adamczyk et al., 2012; Bockstedt et al., 2015; Terwiesch & Ulrich, 2009; Terwiesch & Xu, 2008; von Hippel, 2005). An innovation contest consists of a seeker who is responsible for proposing a specific problem, offering awards, setting the contest duration, and broadcasting an invitation to submit solutions. Solvers who are invited and/or interested in the problem can submit their solutions. When the contest is over, the seeker awards one or more solutions according to their evaluation. Instead of promoting and running the contest by themselves, seekers can also use the services of online platforms to organize innovation contests. Examples of well-known online innovation contest platforms include 99designs (en.99designs.nl) and Logomyway (www.logomyway.com) for design projects, and Topcoder (www.topcoder.com) and Codechef (www.codechef.com) for programming projects.

Compared with collaborative communities, innovation contests feature a competitive relationship among solvers. Although solvers may learn from each other by checking solutions developed by other solvers, and they may be intrinsically motivated to submit solutions, one main goal is winning awards, rather than aggregating contributions of a pool individuals into one best solution. Compared with complementors, the seeker launches an innovation contest not for the immediate aim of making profits but for finding solutions to an innovation challenge, and solvers do not share a common

[2] www.apple.com/itunes
[3] www.clickworker.com

base of software or hardware on which they develop their solutions. Tasks in labor markets are usually well-defined, and the performance of workers can be explicitly evaluated. The problems in innovation contests, on the contrary, are complex and/or novel. High-quality solutions to such kind of problems require creative thinking, expertise, and effortful input of the solvers. Thus, it is the differences in solver relationship (competition or cooperation), task relevance (independently developed or based on a core product or technology), and task specificity (complex and challenging task or routine work) between the innovation contest and other types of crowd-powered innovation approaches that makes innovation contest uniquely suitable for highly challenging technical, analytical, and design problems. Many well-known companies, such as Adidas (Piller & Walcher, 2006), DELL (Poetz & Schreier, 2012), Peugeot (Rohrbeck, Steinhoff, & Perder, 2008), Volvo (Harryson, Dudkowski, & Stern, 2008), and IBM (Bjelland & Wood, 2008), have adopted innovation contests to find creative and innovative solutions for their innovative challenges.

1.2 Improving the Contest Performance

Firms that organize innovation contests are looking for good solutions to their innovation problems. Good solutions can be defined differently contingent on the characteristics of innovation problems. For design projects, online platforms often provide seekers scoring system to help them to indicate their preference toward submitted solutions. According to the meaning of the scores, those solutions can be classified into high-quality, medium-quality, and low-quality. Therefore, contest performance for design projects can be measured by the number of high-quality solutions submitted by solvers. For programming projects, the quality of solutions can be quantified as a scalar with a range (e.g., 0 ~ 100). Thus, the contest performance for programming projects can be conceptualized as the magnitude of such scalar of the best solution.

Examining drivers of innovation contest performance is the main goal of studies on innovation contests. After a literature review, we find that contest design elements, solver characteristics, and the ways that the seeker manages contests can influence contest performance (see Figure 1-1). Contest design elements include factors that are configured or specified before the start of the contest. Solver characteristics are individual traits that can be leveraged by the seeker to influence contest performance. The ways in which the seeker manages contests refer to how the seeker interacts with their solvers.

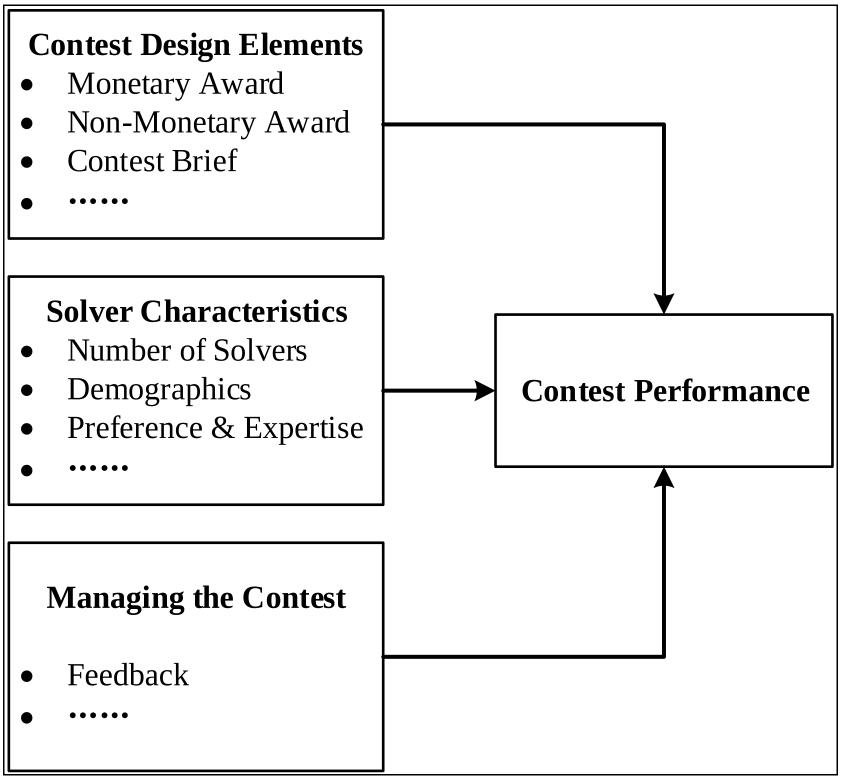

Figure 1–1 Factors that influence the contest performance[4]

One contest design element that is controlled by the seeker, and that can simultaneously influence the efforts of solvers is the monetary award. Motivation theory predicts that individuals can be motivated for multiple goals, such as winning awards, status promotions, or career opportunities (Deci & Ryan, 1980). A motivated solver will be more likely to join the contest, and invest more effort to develop a solution. Consistent with this prediction, Brabham (2010) interviewed solvers in an crowdsourcing platform for t-shirt design, and found that all participants interviewed who had submitted a t-shirt design in the past explicitly mentioned money as a motivating factor for their submissions. Leimeister, Huber, Bretschneider, and Krcmar (2009) evaluated

[4] "Managing the Contest" includes at least two items: "feedback", which is discussed in this section, and "participation level of the seeker", which will be proposed as an avenue for the future research.

solvers' motive of participation, and found that solvers can be extrinsically motivated by the possibility to win monetary awards. Liu, Yang, Adamic, and Chen (2014) found that a higher award results in significantly more solution submissions and higher quality of submitted solutions. Besides this, other studies compared the effect of the award structure on the contest performance. For example, Terwiesch and Xu (2008) focused on two award structures: fixed-price award and performance-contingent award. The former refers to a pre-specified award with a fixed amount, which will be transferred to solvers according to a preannounced award allocation structure. The latter refers to how much award the winner(s) can finally receive is contingent on the seeker's profits. They found that compared with fixed-price award, performance-contingent award results in better solutions, higher profits of seekers, and system efficiency.

Besides the monetary awards, innovation contests also provide the winner other awards. Online platforms for innovation contests usually sort register solvers according to some competence indexes. A higher ranking indicates higher competence, and higher status in the solver community, and may even impact career opportunities. Promoting status, and pursuing career opportunities belong to extrinsic motivations (Roberts, Hann, & Slaughter, 2006). Studies in open source software development found that individual contributors can be motivated by such status and opportunity motives (Lerner & Tirole, 2002; Roberts et al., 2006). Besides this, studies also found that solvers can be motivated by other non-monetary awards, such as improving creative skills, and the love of solver community (Brabham, 2010). Thus, such non-monetary awards can also improve the contest performance.

The third contest design element that can potentially influence the contest performance is the contest brief. Briefing can be defined as a process during which designers negotiate with their clients about the profile of projects (Paton & Dorst, 2011; Ryd, 2004). This profile usually includes the project goal, a ranking of relevant project features, the problem scope, solution scope and resource constraints, and the evaluation criteria (Hey, Joyce, & Beckman, 2007). The brief document is the product of the briefing process, and it refers to a document specifying the background and requirements for a project (Ryd, 2004). The brief of an innovation contest is an important information source for solvers provided by the seeker, and it potentially affects the contest outcomes.

Besides the contest design elements, solver characteristics can also influence the contest performance. The first factor that we need to elaborate on in this part is the number of solvers. The relationship between the number of solvers and contest performance is a long-standing question in innovation contest research. Some studies in economics suggest that as the number of solvers who commit to a contest increases, the likelihood of any one solver winning the contest decreases, which in turn, will undermine the incentives to invest effort to develop solutions, and lower the overall innovation outcomes (underinvestment effect) (Che & Gale, 2003; Fullerton & McAfee, 1999; Taylor, 1995). Others treat innovation contests as a search process. The more solvers a contest has, the broader the search. Then, the likelihood of finding at least one best solution will increase (parallel path effect) (Abernathy & Rosenbloom, 1969; Dahan & Mendelson, 2001). Boudreau, Lacetera, and Lakhani (2011) found that both effects co-exist in innovation contests. As the number of solvers increases, the average score of solutions, which is an indicator of average quality, decreases significantly. This finding is consistent with the prediction of the underinvestment effect. The results showed that the score of the best solution is not significantly undermined when a contest has more solvers. The negative effect of the number of solvers on the performance of the best solution is alleviated by the parallel path effect.

Solvers with different demography variables will behave differently when they are confronted with the same contest, which will finally, affect the contest performance. Bockstedt et al. (2015) examined the effects of the national wealth and the national culture of solvers on the problem-solving effort in innovation contests. They found that solvers from countries with lower GDP per capita, higher performance orientation, or lower uncertainty avoidance will exert more problem-solving effort in innovation contests. GDP per capita negatively moderate the effect of performance orientation on the problem-solving effort. Solvers who are more similar to the seeker in GDP per capita or culture are more likely to win the contest.

In addition to this, solvers' behaviors are different when they have different preference and expertise in innovation contests. Boudreau and Lakhani (2014) designed two groups. One group is formed by workers who sort into the competitive contest regime, the other group has the same work skill distribution, but its workers are unsorted in terms of preference for the competitive contest regime. They found that problem-solving performance doubled when comparing sorted workers with those who were precisely matched on skills but unsorted. This effect was statistically the same as the effect of varying the monetary award from $0 to $1,000. Boudreau, Lakhani, and Menietti (2016) found that high-skilled and low-skilled solvers respond differently to enrolling additional solvers in an innovation contest.

The last dimension that can influence the contest performance is the ways in which the seeker manages contests. Feedback from the seeker to the solvers belongs to such dimension. The effect of feedback on task performance has received considerable attention. Kluger and DeNisi (1996) concluded that if feedback is about task relevant information, it has a consistent positive effect on the task performance. Vidal and Nossol (2011) found that relative performance feedback can lead to a large and long-lasting increase in productivity of workers even without providing monetary award. Jung, Schneider, and Valacich (2010) assessed the effect of feedback on the performance of group idea generation. The feedback of individual performance can create a competitive atmosphere that motivates individuals to match the performance of the best performing members, help to correct illusory performance perceptions, and reduce social loafing by providing positive (negative) reinforcement for high (low) performers. Thus, groups with feedback of individual performance will generate more and better ideas than groups without such feedback. Mihm and Schlapp (2015) investigate three feedback formats: no feedback, public feedback (which all solvers can receive) and private feedback (which only the concerned solvers can receive). They found that which feedback is preferred is contingent on the contest objective (average or best performance of solutions) and the solvers' uncertainty about the outcomes.

1.3 Research Gaps & Questions

Previous studies have already provided many insights about the drivers of contest performance. However, there are still contest design elements and solver characteristics that have not been sufficiently studied yet, but that can also influence contest performance. First, the brief of an innovation contest is an important information source for solvers provided by the seeker, and it potentially affects the contest outcomes. However, former studies in innovation contest have mostly neglected the effect of contest briefs on the contest performance, and little is known about how to develop a brief in order to receive more high-quality solutions. In response to this research gap, we propose the first research question of this thesis:

RQ1: *What is the effect of the contest brief on contest performance?*

Second, as we reviewed above, in innovation contests, individuals with different characteristics behave differently. Solvers who submit solutions in an innovation contest form a solver group. A solver group is more or less diversified, and thus, can be characterized with a diversity level in some solver characteristics (e.g. expertise). It has been revealed that the diversity of work group can affect the group performance (van Knippenberg, De Dreu, & Homan, 2004; van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998). However, little is known about the effect of diversity on contest performance and how to cope with it in practice. Consistent with this research gap, we propose the second research question of this thesis:

RQ2: *What is the effect of the diversity of solvers on contest performance?*

Last, most innovation contest studies treat innovation contests as a one-round competition, and tend to overlook the competition among solvers during the process of the contest. In some contests where solvers are allowed to submit multiple solutions, and the seeker can score these, interim information about the contest performance is generated and available to solvers. Such interim information includes the current number of solvers who have submitted one or more solutions, the current number of high-quality and low-quality solutions. In this case, solvers who consider submitting a new solution can be affected by such interim information. For example, if a contest has already received many high-quality solutions, solvers may invest less effort to develop solutions. Some modeling studies concerned the effect of interim information (Aoyagi, 2010; Ederer, 2010), however, their assumptions are less realistic. In sum, the innovation contests feature dynamics. However, most of studies till now have not shed light on it. For addressing the last research gap, we address the following research questions:

RQ3: *What is the effect of interim information generated during the competition on contest performance?*

1.4 Dissertation Outline & Objective

The objective of this dissertation is focusing on three research questions on how contest performance can be influenced. Mechanisms underlying the answers to these questions are mainly motivation theory and the insights from the studies on work group diversity. The outline of this dissertation is shown in Figure 1-2.

In order to empirically determine these proposed effects, and answer these research questions, we collect data in a well-known online platform of innovation contests for design tasks. This platform, which was founded in 2008, now (up to September-2017) has attracted 206,000 solvers from 195 countries, and have helped over 52,000 well-known companies, startups, and non-profits with logo design, web design, etc. The data include the detail information of contests (e.g., contest briefs, awards amount, awards spots, contest duration), and the behavioral information of seekers and solvers (e.g. when solvers submit which solution, when seekers score which solution with which score). We obtain two datasets. The time span of contests in datasets is from April-2009 to September-2014, and from May-2011 to October-2016.

The rest of this dissertation is organized as follows. Chapter 2 investigates the effect of the contest briefs on the contest performance. Chapter 3 examines the effect of solvers diversity on the contest performance. Chapter 4 models the interim information about the contest performance generated during the competition, and checks its effect on the contest performance. Chapter 5 summarizes our findings and suggests directions for future research. Table 1–1 provides the overview of three empirical chapters (Chapters 2, 3 and 4).

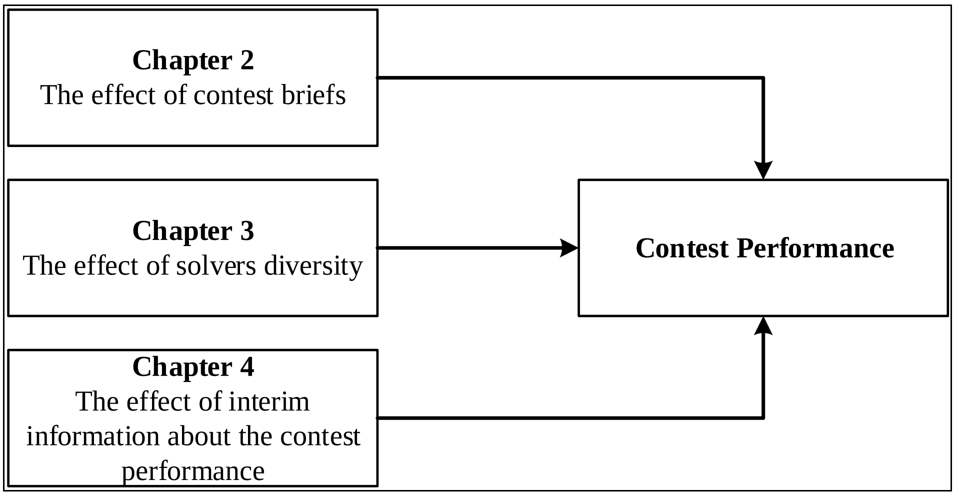

Figure 1–2 Outline of the empirical chapters in dissertation

Table 1–1 Overview of empirical chapters

	Chapter 2	**Chapter 3**	**Chapter 4**
Topic	The effects of the contest briefs on the contest performance	The effects of the diversity of solvers on the contest performance	The effects of the interim information about the contest performance on the contest performance
Level of analysis	Contest level	Contest level	Solver level
Modeling approach	➢ Path model with count dependent variables ➢ Negative binominal regression ➢ Zero-inflated negative binominal regression	Negative binominal regression	Generalized linear mixed models with crossed random effects
Dependent variables	➢ The number of high-skilled solvers ➢ The number of low-skilled solvers The number of high-quality solutions	The number of high-quality solutions	➢ Increment of the number of solvers ➢ Increment of the number of high-quality solutions
Independent variables	➢ The readability of briefs ➢ The length of briefs ➢ The number of high-skilled solvers ➢ The number of low-skilled solvers	➢ Expertise diversity ➢ Resident country diversity ➢ Experience diversity ➢ The uncertainty level of briefs	➢ The current number of solvers ➢ The current number of high-quality solutions ➢ The current number of low-quality solutions
Key results	➢ Brief readability and length directly and indirectly influence contest performance. ➢ Contests with readable and/or longer briefs tend to have more high-quality solutions.	➢ Diversity has a nonlinear effect on contest performance. ➢ The uncertainty level of briefs moderates the curvilinear relationships	➢ The current number of solvers and the current number of high-quality solutions are mutual affected. ➢ Low-quality solutions influence contest performance.

2 The Impact of Innovation Contest Briefs on the Quality of Solvers and Solutions[5]

Abstract: As firms increasingly adopt online contests to improve their innovation efforts, research is needed on what design factors make a contest successful. We examine the effects of the contest brief on contest performance, with a focus on the length and readability of the brief, to test for both direct and indirect effects. Both brief readability and brief length have direct and indirect effects on contest performance, and their indirect effects are determined by their effects on the numbers of high-skilled and low-skilled solvers that a contest attracts. Furthermore, the combined effects of both brief characteristics are positive and these effects increase as the brief becomes more readable and longer. Finally, we find that both high- and low-skilled solvers can submit high-quality solutions, but this likelihood is significantly larger for high-skilled solvers. The findings suggest that briefs affect contest performance, making them an important element in the design of innovation contests.

[5] This Chapter is based on the working paper Feng Hu, Tammo Bijmolt, Eelko Huizingh. *The Impact of Innovation Contest Briefs on the Quality of Solvers and Solutions*. Groningen, The Netherlands: University of Groningen. DOI: 10.13140/RG.2.2.30159.07849

2.1 Introduction

With rapid globalization and advances in network technologies, firms and individuals are increasingly connected, making it much easier to exchange ideas. Along with this trend, more firms are reaching out to external parties to gather input that is useful for their innovation projects. One way to do so is through innovation contests (Boudreau & Lakhani, 2013). Innovation contests can efficiently and economically provide solutions for innovation problems because they induce competition among solvers and award only the best solutions (Terwiesch & Xu, 2008). Many well-known firms have adopted innovation contests to generate novel ideas, such as Dell, Best Buy, BBC, CNN, BMW, and Adobe (Huang, Singh, & Srinivasan, 2014).

Innovation contests involve several steps. A firm (also known as the "seeker") searching for solutions to an innovation problem creates a contest brief, which is a description of the problem and the requirements for potential solutions. Then, the seeker determines the other contest characteristics, such as the award(s) and the contest duration, and posts the contest on either its own website or a third-party website that acts as a platform for innovation contests. Interested "solvers" can access the contest and submit their solutions. When the contest is over, the seeker selects one or more high-quality solutions to award. Examples of well-known online innovation contest platforms include 99designs (en.99designs.nl) and Logomyway (www.logomyway.com) for design projects and Topcoder (www.topcoder.com) and CodeChef (www.codechef.com) for programming projects.

To attract high-quality solutions, an innovation contest must be sufficiently attractive for solvers to invest their time and effort. Solvers can be motivated by various factors, including the opportunity to express creativity and competence, a sense of accomplishment, the probability of winning monetary awards, status within communities, and/or career opportunities (Deci & Ryan, 1980; Vallerand, 1997). Previous studies of innovation contests provide many insights into whether and how the contest awards (Liu et al., 2014; Terwiesch & Xu, 2008; Toubia, 2006), the number of solvers (Boudreau et al., 2011; Che & Gale, 2003; Fullerton & McAfee, 1999), feedback from the seeker (Jung et al., 2010; Vidal & Nossol, 2011), and cultural factors (Bockstedt et al., 2015) affect contest performance. Thus, from the seeker's perspective, studies of innovation contests have yielded many guidelines for designing successful contests. However, previous research has neglected one essential aspect of the innovation contest, namely, the contest brief.

Briefing has been studied in related areas. Design studies define briefing as a process during which designers negotiate with their clients about the profiles of projects (Paton & Dorst, 2011; Ryd, 2004). The profile usually includes the project's goal, a ranking of relevant project features, the problem scope, the solution scope, resource constraints, and evaluation criteria (Hey et al., 2007). The brief is the product of the briefing process, and it refers to a document specifying the background and requirements for a project (Ryd, 2004). The brief of an innovation contest is an important information source that a seeker provides to potential solvers, and it can affect contest outcomes. In this paper, we propose and test whether and how characteristics of the contest brief affect contest performance (see Figure 2-1).

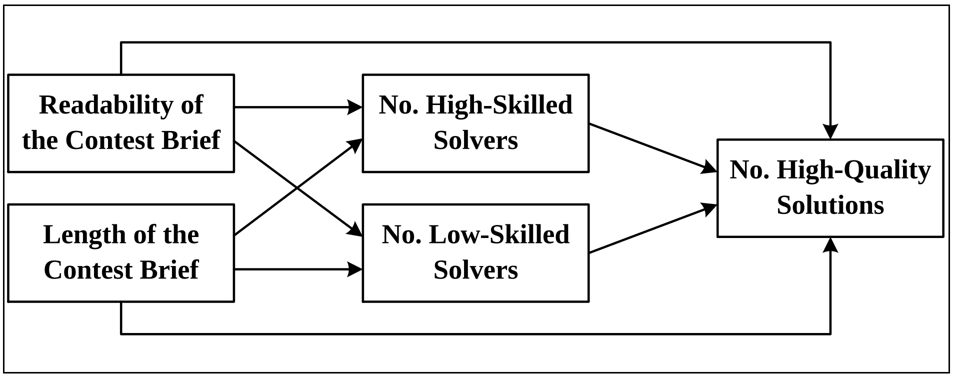

Figure 2–1 Research framework

We focus on two main brief characteristics—namely, the readability and the length of the contest brief—and relate these to contest performance. Ultimately, contest performance is conceptualized as the number of high-quality solutions a contest receives, but we suggest that this relationship can be mediated by the number of solvers who submit a solution to the contest. Because the brief can have different effects on attracting different kinds of solvers, we distinguish between the numbers of high-skilled and low-skilled solvers submitting a solution to the contest.

We test the proposed relationships (see Figure 2-1) with data from an innovation contest platform for design projects. The database contains 3,931 contests, 28,325 solvers, 591,212 observations of solution submitting, and 319,931 observations of solution scoring. We use the scores of Flesch Reading Ease (Flesch, 1948) and Flesch–Kincaid Grade Level (Kincaid, Fishburne, Rogers, & Chissom, 1975) to quantify the readability of the contest brief and use the number of words to measure the length of the contest brief. Controlling for the effect of other contest design characteristics, the results from negative binominal regression, zero-inflated negative binominal regression, and path analysis reveal the following:

1. Both brief readability and brief length directly influence the contest performance.

2. Both brief characteristics indirectly influence the contest performance through their effects on the numbers of high-skilled and low-skilled solvers.

3. The combined effects of both brief characteristics suggest that a contest with a long and easy-to-read brief will attract more high-quality solutions.

4. The combined effects of both brief characteristics increase as the brief becomes more readable and longer.

5. Both high-skilled and low-skilled solvers can submit high-quality solutions, though this likelihood is significantly greater for high-skilled solvers.

Our findings suggest that the contest brief gives the seeker an important means to leverage contest performance. A contest with a long and easy-to-read brief tends to receive more high-quality solutions. Moreover, along with well-studied characteristics such as the awards, the brief is a useful tool that can attract and motivate potential solvers to join a contest. Our findings show that different briefs attract different kinds of solvers in terms of their skill level. The seeker of a contest can proactively attract high or low skilled solvers by deliberately developing a brief with the proper level of readability and/or length, according to their goal.

We structure the remainder of this paper as follows: In Section 2.2, we review relevant literature and discuss our conceptual model and hypotheses. In Section 2.3, we detail the data and estimation strategies. We report the empirical results in Section 2.4

and discuss the contributions and managerial implications of the study in Section 2.5.

2.2 Literature & Hypotheses

2.2.1 Readability of briefs

Readability refers to the characteristics that make a text comparatively easier to read. Text elements that affect readability include content (e.g., propositions, organization, coherence), style (e.g., semantic, syntactic elements), design (e.g., typography, illustrations), and structure (e.g., chapters, headings, navigation) (Gray & Leary, 1935). Cognitive theorists and linguists have long tried to develop practical methods to quantify the effects of these factors on overall readability. However, these methods are not applicable for readers with different reading skill levels, except for methods related to writing style (DuBay, 2004). Therefore, in this study, we focus on readability in terms of writing style and define *readability* as the ease of understanding or comprehension of a text due to the style of writing (Klare, 1963). This definition suggests that seekers can influence the readability of their contest brief by changing its writing style. A text is more readable if, for example, its average sentence length in words is shorter, the percentage of easy words is higher, and/or it contains more explicit sentences (Gray & Leary, 1935). The readability of texts can be measured numerically using various formulas. The most tested, used, and reliable of these is the classic Flesch Reading Ease formula and its variant for determining reading grade (Chall, 1958; DuBay, 2004; Klare, 1963).

A brief that is easier or more difficult to read may be attractive to solvers with different skill levels. This effect may be due to the motivation derived from the interaction between solvers and briefs. The two main types of solver motivation are intrinsic and extrinsic (Loch, Huberman, & Stout, 2000; Vidal & Nossol, 2011; von Hippel, 2005). Intrinsically motivated solvers perform an activity because they derive pleasure and satisfaction from doing so (Vallerand et al., 1993). Studies suggest people have a basic need for competence (White, 1959) and are intrinsically motivated to engage in challenging activities because they seek to meet this basic need (Deci & Ryan, 1985). Others define intrinsic motivation as a kind of subjective experience that happens when people perform an activity (Csikszentmihalyi, 1988). This experience is characterized by high engagement in the activity, unity of action and awareness, high level of attention to the stimulation, and feelings of selflessness and full mastery. People experience these feelings only if they have the ability to persevere through the challenge (Eccles & Wigfield, 2002). Achieving this state and these feelings necessitates a balance between the challenge level of the contest and the skill level of the individual (Csikszentmihalyi, 1975). High-skilled (low-skilled) solvers will experience such feelings when they are confronted with a bigger (smaller) challenge. When low-skilled solvers are confronted with a big challenge, they may feel anxiety rather than motivation (Nakamura & Csikszentmihalyi, 2014). Thus, people can be motivated to engage in an activity by their need for a sense of accomplishment or competence. This reasoning suggests that both high-skilled and low-skilled solvers can be intrinsically motivated by challenging tasks, as long as the level of challenge provides an appropriate match for the solver's skill level.

The readability of briefs determines the setting in which solvers can derive more or less intrinsic motivation. An innovation contest with a difficult-to-read brief can be regarded as a highly challenging task. Thus, high-skilled solvers will be more likely to regard such a contest as a challenge that matches their ability, and they will be more attracted and intrinsically motivated to join such a contest. Therefore, a contest with a less readable brief may attract more high-skilled solvers. In contrast, low-skilled solvers are more likely to consider a contest with a difficult-to-read brief as a challenge that is beyond their ability. They may feel that they are less likely to derive a sense of accomplishment or competence by joining such a contest. Therefore, contests with less readable briefs will attract fewer low-skilled solvers. In line with this rationale, we formulate the following hypotheses:

HYPOTHESIS 1. *Innovation contests with less readable briefs attract more high-skilled solvers.*

Hypothesis 2. *Innovation contests with less readable briefs attract fewer low-skilled solvers.*

Next to an effect on the number of solvers, the readability may also directly affect the number of high-quality solutions. Compared with the traditional innovation process in organizations, solvers in innovation contests are geographically and hierarchically decentralized and physically and cognitively independent (Bayus, 2013). For a seeker to organize a successful contest, solvers must be fully informed by relevant knowledge and information (Lakhani, Lifshitz-Assaf, & Tushman, 2012). The brief the seeker provides at the beginning of an innovation contest is often the only information source about the innovation problem that is available to solvers. The brief clarifies the objective of the project, the environment in which solutions will be used, and the criteria for assessing solutions. As innovation contest platforms tend to stress, seekers should provide detailed briefs to attract the highest-quality solutions. We conjecture that if a brief is more readable, its message will be easier to understand by the solver, which facilitates solvers' ability to develop high-quality solutions. Thus, contests with more readable briefs will receive more high-quality solutions. We formulate the following hypothesis on the direct effect of the readability of the brief:

Hypothesis 3. *Innovation contests with more readable briefs receive more high-quality solutions.*

2.2.2 Length of briefs

In addition to readability, another characteristic of the brief that the seeker can determine is its length. The length of a text is often regarded as an important dimension of web page complexity (Geissler, Zinkhan, & Watson, 2001). More text means a higher density of information cues in the task stimulus, and task stimuli with a higher density of information cues tend to be perceived as more complex (Nadkarni & Gupta, 2007). As we reasoned above, the brief is the main information source for the solver when developing solutions. The solver reads the brief in order to be able to develop high-quality solutions, and ultimately to win the contest. Therefore, a goal-directed solver will examine the text for its informative value and utility. Complex cues complicate reaching their goal, and thus a solver may not be willing to invest extra effort to process them (Wolfinbarger & Gilly, 2001). Previous research has found that goal-directed users are less satisfied with a web page with longer text (Nadkarni & Gupta, 2007), they move away from such a stimulus and stop browsing the web page (Deng & Poole, 2010). Before solvers get to the point at which they are ready to develop a solution, they need to invest effort in processing the brief and finding useful information. Longer briefs require them to invest more effort. This extra mental resource requirement may make them less satisfied, which in turn will make the contest less attractive to solvers. Thus, all else being equal, briefs with longer texts will be less attractive to solvers. Therefore, we posit:

HYPOTHESIS 4. *Innovation contests with longer briefs attract fewer high-skilled solvers.*

HYPOTHESIS 5. *Innovation contests with longer briefs attract fewer low-skilled solvers.*

However, if solvers decide to join a contest and start developing and submitting solutions, a brief with a long text can be helpful, since the brief provides solvers with key information about the innovation project and the requirements for qualified solutions. The longer a brief, the more detailed and complete the information, which makes it easier for solvers to develop high-quality solutions. Thus, contests with longer briefs are likely to receive more high-quality solutions. In line with this reasoning, we propose the following hypothesis on the direct effect of the length of the brief:

HYPOTHESIS 6. *Innovation contests with longer briefs receive more high-quality solutions.*

2.2.3 Solvers and contest performance

In innovation contests, solvers are expected to develop solutions. The relationship between the number of solvers and contest performance has been studied extensively. Various studies from different perspectives propose mechanisms for this relationship.

Studies in economics, for example, suggest that a larger number of solvers implies lower contest performance because a large number of solvers reduces the likelihood of any one solver winning the contest, which undermines solvers' extrinsic motivation to invest effort and lowers the overall innovation outcomes (Boudreau et al., 2011; Che & Gale, 2003; Fullerton & McAfee, 1999; Taylor, 1995; Terwiesch & Xu, 2008). In line with predictions of this effect, more solvers should generate fewer high-quality solutions. However, other studies view innovation contests as a search process. More solvers means a broader search for the best solution, which results in a higher likelihood of finding at least one very good solution (Dahan & Mendelson, 2001; Terwiesch & Xu, 2008). Empirical studies reveal that though the number of solvers is negatively correlated with the average quality of solutions a contest receives, its negative effect on the quality of the best solution is not significant (Boudreau et al., 2011). Following these seemingly competing rationales, we conjecture that a contest with a larger number of solvers may receive solutions with a lower average quality. However, an individual's likelihood of developing a high-quality solution is not substantially undermined, so contests with more solvers will receive more high-quality solutions. Taken together, we formulate the following hypotheses:

HYPOTHESIS 7. *Innovation contests with more high-skilled solvers receive more high-quality solutions.*

HYPOTHESIS 8. *Innovation contests with more low-skilled solvers receive more high-quality solutions.*

Hypotheses 7 and 8 predict positive effects of both the number of high- and low-skilled solvers on the number of high-quality solutions. However, we expect the magnitude of these two effects to differ. Intuitively, high-skilled solvers are more likely to develop high-quality solutions than low-skilled solvers. Thus, the positive effect of the high-skilled solvers will be greater than that of the low-skilled solvers. Accordingly, we formulate a final hypothesis:

HYPOTHESIS 9. *The positive effect of the number of high-skilled solvers on the number of high-quality solutions is greater than that of the number of low-skilled* *solvers.*

The framework in Figure 2-2 summarizes the preceding discussion and shows the hypothesized relationships among the two characteristics of briefs (readability and length), the numbers of high-skilled and low-skilled solvers, and the number of high-quality solutions.

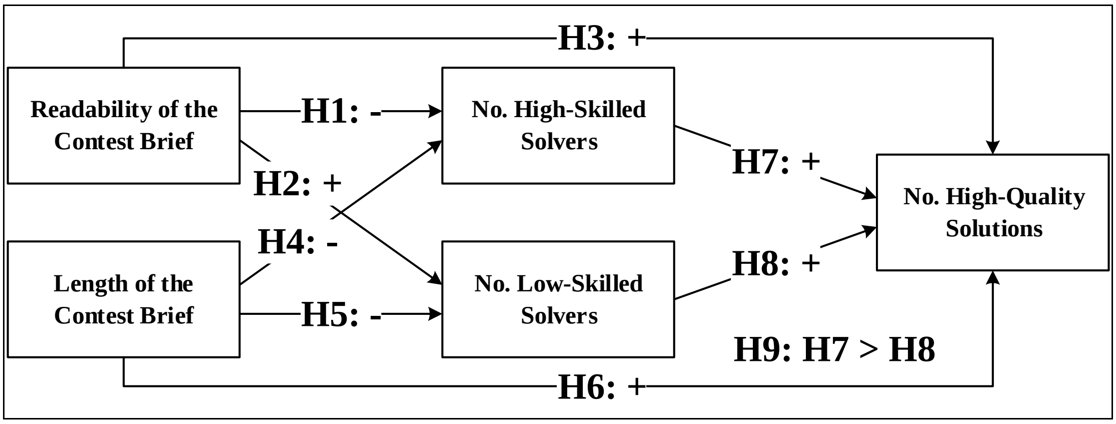

Figure 2–2 Research framework and hypotheses

2.3 Data & Methods

2.3.1 Innovation contests process and data

We obtained data from the website of a well-known innovation contest platform. On this website, seekers can host contests for various kinds of design projects. The process of running contests on the website is as follows: At the start, the seeker provides the contest brief, which describes the project and the type of solutions the seeker wants. The seeker also specifies the number of awards, the monetary amount of each award, and the contest duration. During the contest, solvers can freely join and submit their solutions. The submitted solutions are visible to all solvers. In addition, the seeker can assign scores to solutions (1 to 5), indicating the extent to which the seeker appreciates a solution. When a contest is over, seekers can award one or more solutions. The database we use contains 3,931 contests for graphic and web design projects, 28,325 solvers, 591,212 solution submissions, and 319,931 observations of solution scoring.

2.3.2 Concept measurement and variables

Studies in language provide multiple formulas for measuring the readability of a text. The most commonly used formulas are the Flesch–Kincaid Grade Level and the Flesch Reading Ease (Wang, Miller, Schmitt, & Wen, 2013). Both formulas have been applied for measuring the readability of online texts (Candelario, Vazquez, Jackson, & Reilly, 2017), academic articles (Sawyer, Laran, & Xu, 2008), and popular juvenile books (Pettis, 2008). According to both formulas, fewer words per sentence and/or fewer syllables per word indicate that a text is more readable. Readability scores are calculated with the following formulas (Flesch, 1948; Kincaid et al., 1975):

$$\begin{cases} \text{Flesch-Kincaid Grade Level}=0.39\left(\dfrac{\text{total words}}{\text{total sentences}}\right)+11.8\left(\dfrac{\text{total syllables}}{\text{total words}}\right)\text{-}15.59 \\ \text{Flesch Reading Ease}=206.835\text{-}1.015\left(\dfrac{\text{total words}}{\text{total sentences}}\right)-84.6\left(\dfrac{\text{total syllables}}{\text{total words}}\right) \end{cases}.$$

Both scores are negatively correlated: a lower Flesch–Kincaid Grade Level and a higher Flesch Reading Ease indicate that the text is easier to read. In this study, we use both scores to measure the readability of a contest brief. The scores are calculated using the Python package “textstat.” Furthermore, following studies in web page complexity (Geissler et al., 2001; Nadkarni & Gupta, 2007), we measured the length of the brief by the number of words in the brief.

We derive the skill level of solvers from their performance in previous contests to which they submitted solutions. For each solver, we have data on the number of solutions submitted and the number of solutions awarded. We calculate the ratio of awarded solutions for each solver, which equals the number of awarded solutions divided by the number of submitted solutions. To classify solvers into high-skilled and low-skilled categories, we set a threshold and specify that solvers with a ratio of awarded solutions that is smaller than (larger than or equal to) this threshold are low-skilled (high-skilled) solvers. We have to balance between classifying only outstanding solvers with a high success rate as high-quality solvers versus making the group of high-quality solvers too large. Therefore, we aim to label the top-10 percent of the solvers as high-quality solvers, which requires a threshold of 0.15 (see Table 2–1). In addition, we test our model with multiple thresholds (0.11, 0.13, 0.15, 0.17, and 0.19) to determine the robustness of our findings. In the data set, 53% of awarded solutions received the maximum score of 5, and 38% received a score of 4. Therefore, we classify solutions with a score of 4 or 5 as high-quality solutions and solutions with scores between 1 and 3 as low-quality ones.

In addition to the key variables in the conceptual framework, we include several control variables to account for heterogeneity at the contest level. First, there is ample evidence that contest awards determine solver motivation, and contest performance (Terwiesch & Xu, 2008). Thus, we include the average award value, the number of award spots, and whether or not awards are assured to control for the effect of awards on the numbers of high-skilled and low-skilled solvers and contest performance. Award assured is a dummy variable that equals to 1 if the seeker has guaranteed that the award will be offered to the best solution(s) regardless of its quality, and 0 if otherwise. Second, solvers in contests with a longer duration have more opportunities (time) to develop high-quality solutions. Thus, we include contest duration to control for this possible effect. Third, there are two types of design contests in our data, graphic and web design projects. To control for possible differences between these types of contests, we include contest category as a control variable, which equals 1 for graphic design projects and 0 for web design projects. Table 2–1 shows the descriptive statistics of both the key variables and the control variables.

Table 2–1 Descriptive statistics per contest

Variables	Mean	S.D.	Min	Max
Number of high-quality solutions	17.68	25.83	0	433
Number of high-skilled solvers (ratio = 0.11)	5.44	4.94	0	85
Number of high-skilled solvers (ratio = 0.13)	4.63	4.63	0	73
Number of high-skilled solvers (ratio = 0.15)	4.14	4.52	0	70
Number of high-skilled solvers (ratio = 0.17)	3.54	4.43	0	62
Number of high-skilled solvers (ratio = 0.19)	3.17	4.31	0	58
Number of low-skilled solvers (ratio = 0.11)	37.35	42.51	0	906
Number of low-skilled solvers (ratio = 0.13)	38.16	42.90	0	918
Number of low-skilled solvers (ratio = 0.15)	38.65	43.09	0	921
Number of low-skilled solvers (ratio = 0.17)	39.25	43.22	0	929

Number of low-skilled solvers (ratio = 0.19)	39.62	43.32	0	933
Flesch Reading Ease (unit:10)	6.74	0.99	2.11	9.62
Flesch–Kincaid Grade Level	7.59	2.02	2.10	21.20
Length brief (number of words/100)	5.09	3.62	0.21	48.52
Number of awards	1.32	0.80	1	13
Average awards (unit: $)	657.04	304.06	85.71	5000
Award assured	0.31		0	1
Contest duration (unit: day)	12.13	6.46	0.16	98.74
Contest category	0.64		1	1

2.3.3 Model and estimation

To test our hypotheses (see Figure 2-2) regarding the effects of readability and length of briefs, we use an econometric path model with three dependent variables: the number of high-skilled solvers, the number of low-skilled solvers, and the number of high-quality solutions. Each of these variables is a so-called count variable. When modeling count variables, issues of overdispersion and zero-inflation should be considered (Hilbe, 2014). Overdispersion refers to the presence of larger variability in the data than would be expected based on a given model. When modeling count variables, the Poisson distribution is the most popular distribution. However, this distribution assumes an equal mean and variance. If the variance exceeds the mean by a great deal, overdispersion appears. In such cases, the negative binomial distribution can account for the extra variance compared with the mean. Table 2–1 shows that the variances of high-skilled solvers, low-skilled solvers, and high-quality solutions are much larger than the corresponding means. Thus, compared with the Poisson model, the negative binominal model is more suitable for our data. Zero-inflation refers to the situation in which the zero value in the data is due to two different processes. Taking the number of high-quality solutions as an example, zero values can be the result of solvers joining the contest and of solvers not joining the contest. If solvers do not join, the number of high-quality solutions is, by definition, zero. If solvers join the contest, the number of high-quality solutions is the outcome of a count process, and zero means that solvers have not submitted any solutions that are scored by the seeker as high-quality. Zero-inflated models use a logit model to model the two processes and a negative binominal model or Poisson model to model the count process (A. C. Cameron & Trivedi, 2010).

To empirically determine which specification is suitable to model the three dependent variables, we estimate and compare four count regression models (Poisson, negative binomial, zero-inflated Poisson, and zero-inflated negative binomial), using the Bayesian Information Criterion, Akaike Information Criterion, residual fit, and Vuong test if applicable (Long & Freese, 2014). Consistent with the research framework in Figure 2-2, we select independent variables for each dependent variable. We also include control variables as independent variables. For zero-inflated models, we use the awards assured variable as an explanatory variable to explain the zero-inflated component. We use the Flesch Reading Ease to measure the readability of briefs. The model fits[6] show that the negative binomial model is preferred for modeling the numbers of high-skilled and low-skilled solvers, and the zero-inflated negative binomial model is more suitable for modeling the number of high-quality solutions. Thus, in the path model, we use a negative binominal model to model the numbers of high-skilled and low-skilled solvers and a zero-inflated negative binomial model for the number of high-quality solutions, and we estimate the three equations simultaneously. The paths are configured as they appear in Figure 2-2.

2.4 Empirical Results

In this section, we first report the path analysis results and then the marginal effects of readability and length of the brief on the number of high-quality solutions and the number of high-skilled and low-skilled solvers. Then, we conduct several robustness analyses to check the reliability of our findings.

[6] We do not include the results of fit comparisons in the text to save space. The results can be referred to in Appendix A.

2.4.1 Path analysis

Table 2–2 contains the results of the path analysis. For the identification of high-skilled and low-skilled solvers, we use the ratio threshold of 0.15, and we measure the readability of briefs with the Flesch Reading Ease score. The results using lower and higher thresholds (0.11, 0.13, 0.17, and 0.19) to define the skill level of solvers and the results using the Flesch–Kincaid Grade Level to measure the readability of briefs are highly similar to those in Table 2–2 (see Appendix B; note again that the Flesch Reading Ease score and Flesch–Kincaid Grade Level are negatively correlated).

Table 2–2 The effects of readability and length of briefs on contest performance: results of the path model

Model #	Model 1	Model 2	Model 3
Dependent Variable:	# High-skilled solvers	# Low-skilled solvers	# High-quality solutions
Readability: Flesch-Kincaid reading ease (unit: 10)	-0.076***	0.038**	0.068**
	(-5.109)	(3.434)	(3.134)
Length of brief (unit: 100)	0.000	-0.021***	0.059***
	(-0.114)	(-5.751)	(10.086)
No. high-skilled solvers (ratio=0.15)			0.021***
			(3.624)
No. low-skilled solvers (ratio=0.15)			0.004***
			(5.455)
No. awards (centered by 1)	0.088***	0.125***	0.132***
	(5.129)	(6.916)	(5.882)
Average award (unit: $, normalized)	0.200***	0.229***	0.078**
	(13.430)	(15.785)	(3.060)
Award assured (0: no, 1: yes)	-0.450***	0.300***	0.584***
	(-15.999)	(12.246)	(14.090)
Contest duration (unit: day, normalized)	-0.003	0.115***	0.043*
	(-0.181)	(9.883)	(2.068)
Category: graphic (0: web, 1: graphic)	0.674***	1.526***	0.384***
	(22.577)	(63.719)	(7.877)
Constant	1.543***	2.159***	1.317***
	(15.449)	(28.683)	(8.762)
Over-dispersion			
Constant	-0.334***	-0.391***	0.048***
	(-27.812)	(-43.454)	(33.189)
Zero-inflated			

Award assured (0: no, 1: yes)	-14.025***
	(-28.430)
Constant	-2.736***
	(-17.914)
Test	
No. high-skilled Solvers - No. low-skilled Solvers	0.018**
	(2.882)

t statistics in parentheses, size of the sample: 3,931

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 1 shows that the effect of the Flesch Reading Ease score on the number of high-skilled solvers is significant and negative, while the effect of brief length is very small and not significant. Thus, the results support H1 but not H4. Contests with a less readable brief tend to attract more high-skilled solvers; the length of the brief does not influence the number of high-skilled solvers. Model 2 reports estimates of the effects on the number of low-skilled solvers. The coefficient of the Flesch Reading Ease score is significant and positive, while brief length is significant and negative, suggesting that contests with more readable or shorter briefs attract more low-skilled solvers, consistent with both H2 and H5.

Model 3 includes the results for contest performance, measured as the number of high-quality solutions. The coefficients of the Flesch Reading Ease score and brief length are both positive and significant, indicating that contests with more readable or longer briefs tend to receive more high-quality solutions. The effects of the numbers of low-skilled and high-skilled solvers are positive and significant as well, which means that more high-skilled solvers and more low-skilled solvers both lead to an increase in high-quality solutions. We compare the magnitudes of both positive effects by determining the difference between the coefficient of “Number of high-skilled solvers” and the coefficient of “Number of low-skilled solvers” and its significant level. The results (difference = 0.018, $t = 2.882$, $p < 0.01$) reveal that the coefficient of high-skilled solvers is significantly larger than the coefficient of low-skilled solvers. Thus, high-skilled solvers are more likely to contribute high-quality solutions than low-skilled solvers are. In summary, model 3 provides support for H3, H6, H7, H8, and H9. Figure 2-3 provides an overview of all our findings.

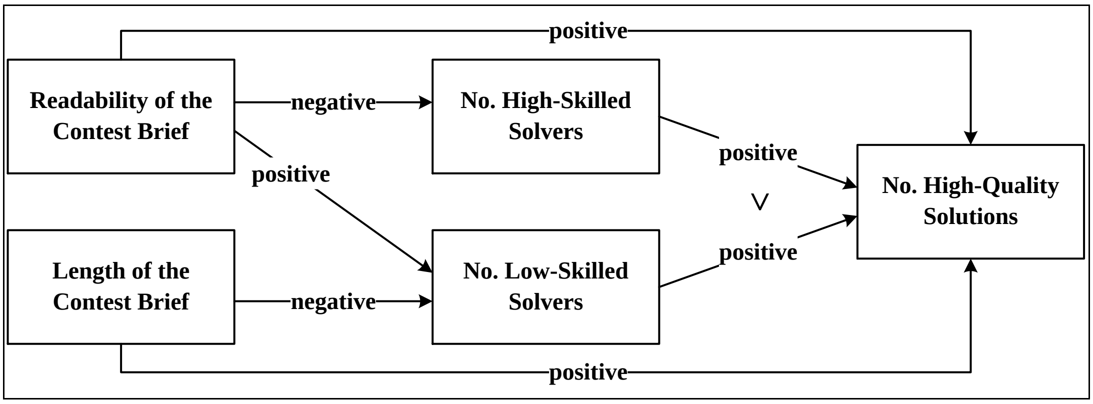

Figure 2–3 Results of the path model: significant effects

Besides the results shown in Figure 2-3, we find multiple significant effects of the contest characteristics that are included as control variables. First, Model 1 shows that contests with more awards, higher average awards, and awards not being assured attract more high-skilled solvers, and contests for graphic design attract more high-skilled solvers than contests for web design. Second, the results in Model 2 show that contests with more awards, higher average awards, awards being assured, and longer duration attract more low-skilled solvers. Furthermore, contests for graphic design also attract more low-skilled solvers than contests for web design. The contest characteristics also influence the number of high-quality solutions. Contests with more awards, higher average awards, awards assured, and longer duration tend to receive more high-quality solutions, and contests for graphic design receive more high-quality solutions than contests for web design.

2.4.2 Total effects on high-quality solutions

As we have proposed and tested in the previous sections, contest briefs with different writing styles attract different numbers and types of solvers in terms of their skill level, which in turn affects contest performance. Because contest briefs provide solvers with useful information, the brief characteristics also directly influence contest performance. Therefore, in our conceptual model, readability and length of the brief both directly and indirectly influence the number of high-quality solutions (see Figure 2-3). The combined effect has important managerial implications for how to develop briefs to improve contest performance. However, the combined effect is not obvious, because some direct and indirect effects differ in their direction. For example, length of the brief has a direct and positive effect on the number of high-quality solutions, but it indirectly affects the number of high-quality solutions, by decreasing the number of low-skilled solvers. In the case of linear models, researchers often report statistics such as the degree of mediation, but such statistics cannot be computed directly for the negative binomial and zero-inflated negative binomial models used in this study. Therefore, to derive combined effects, we conduct a simulation analysis and calculate elasticities and marginal effects (predicted change in the dependent variable after a unit change in the explanatory variable) for both brief characteristics. Appendix C describes the method used to derive the elasticities and marginal effects. We depict these elasticities and marginal effects in Figure 2-4.

Figure 2-4 provides the following insights. First, the elasticity and the marginal effect of the Flesch Reading Ease score are consistently greater than zero and increase as briefs become more readable. When the Flesch Reading Ease score is 40 (indicating a less readable brief), a 1% improvement in readability leads to a 0.3% (0.3 × 1%) change in the predicted number of high-quality solutions. When it increases from 40 to 44,[7] the number of high-quality solutions increases with approximately 1.6. When the Flesch Reading Ease score is 80 (indicating a fairly easy to read brief), a 1% improvement leads to a nearly 0.6% (0.6 × 1%) change in the number of high-quality solutions. When it changes from 80 to 84, the number of high-quality solutions increases with approximately 2.3. As Figure 2-3 shows, readability can indirectly influence contest performance in both a positive and negative way, which complicates the comparison of the direct and the indirect effects of readability. We conclude that the negative effect of readability on the contest performance is dominated by the positive effect.

Second, the elasticity and the marginal effect of brief length are consistently greater than zero, and they increase as briefs become longer. When a contest brief contains 1,000 words, a 1% increase in word count leads to a 0.5% (0.5 × 1%) change

[7] The marginal increase of the readability measure is set to 4 when deriving the marginal effect of readability (see Appendix C).

in the number of high-quality solutions. When the number of words increases from 1,000 to 1,252,[8] the number of high-quality solutions increases with approximately 2. When a contest brief contains 3,000 words, a 1% increase in word count to a 1.7% (1.7 × 1%) change in the number of high-quality solutions. When the number of words increases from 3,000 to 3,252, the number of high-quality solutions increases with approximately 6. Figure 2-3 shows that brief length has both a negative indirect effect and a positive direct effect on contest performance. However, the combined effect of brief length is positive, indicating that its direct effect is larger than its indirect effects.

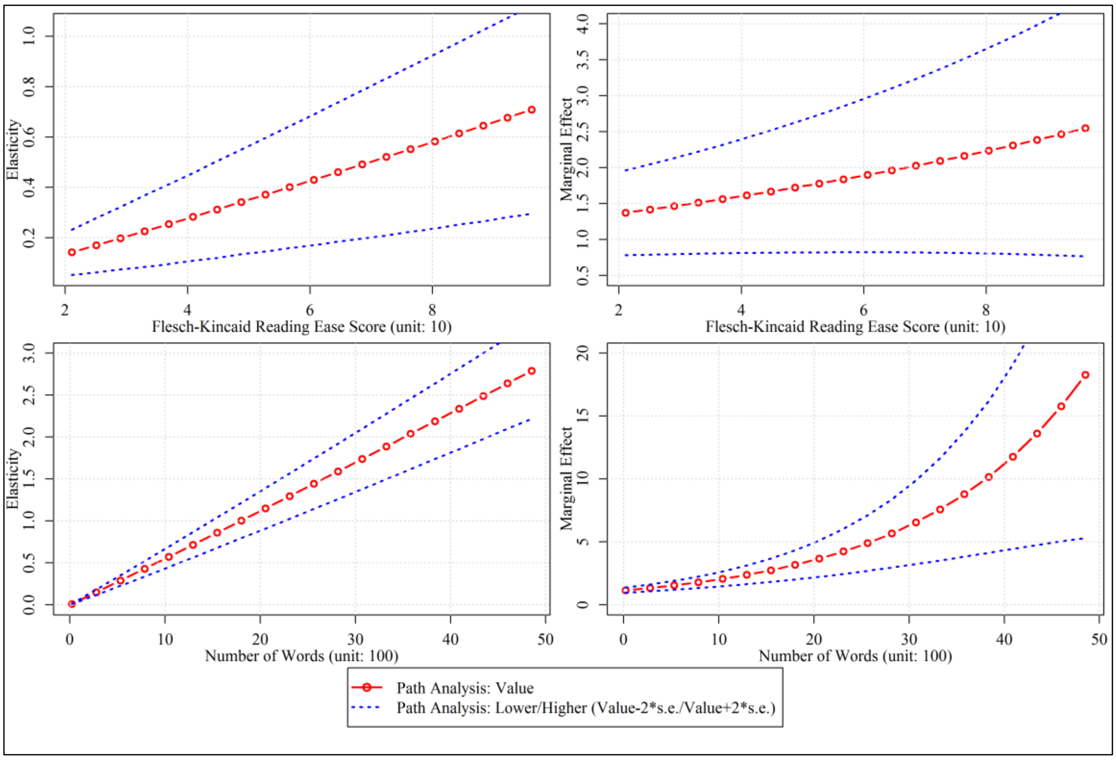

Figure 2–4[9] Total effects of readability and brief length on the number of high-quality solutions

2.4.3 Direct effects on high- and low-skilled solvers

Consistent with the simulation method for calculating the total effects on high-quality solutions (see Appendix C), we also derive the elasticity and the marginal effect of both brief characteristics on the number of high- and low-skilled solvers in Figures

8 The marginal increase of brief length is set to 252 when deriving the marginal effect of brief length (see Appendix C).

9 In Figure 2-4, "Path analysis: value" refers to corresponding estimated elasticities or marginal effects. "Path analysis: upper" ("path analysis: lower") refers to corresponding estimated elasticities or marginal effects plus (minus) two times of their estimated standard errors. The same below.

2-5 and 2-6. In Figure 2-5, we find that the elasticity and the marginal effect of readability on the number of high-quality solutions is negative, and it will become more negative as the brief becomes more readable. The effect of brief length on the number of high-quality solutions is not significant. Figure 2-6 shows that the elasticity and the marginal effect of readability on the number of low-quality solutions is positive, and it will become more positive as the brief becomes more readable. The effect of brief length on the number of low-quality solutions is negative. As the brief becomes longer, the elasticity of this effect becomes more negative, while its marginal effect tends to be less negative.

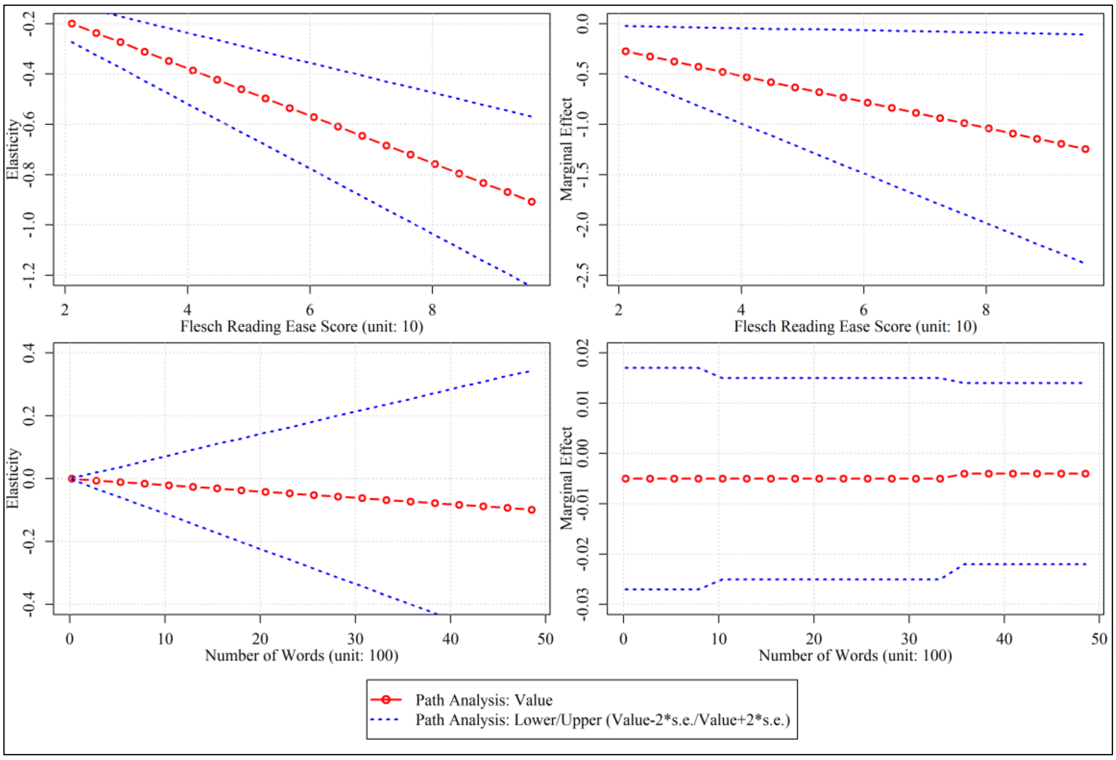

Figure 2–5 Direct effects of readability and brief length on the number of high-skilled Solvers

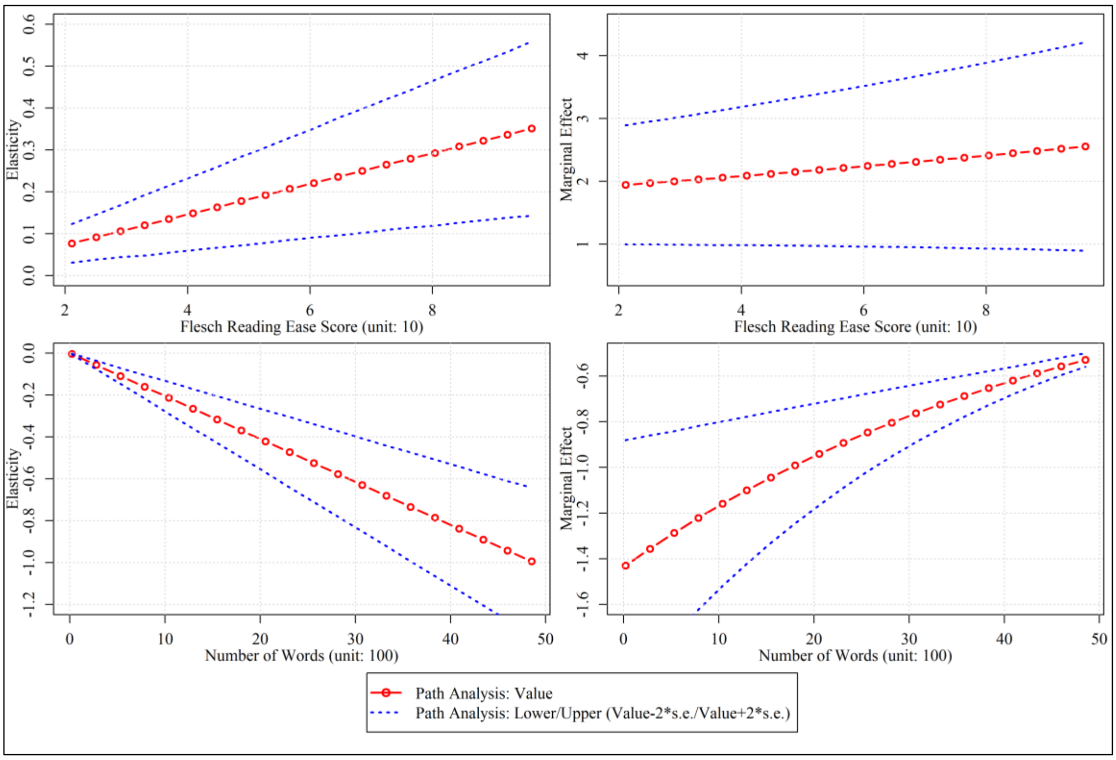

Figure 2–6 Direct effects of readability and brief length on the number of low-skilled solvers

2.4.4 Robustness checks

First, we applied lower and higher thresholds (0.11, 0.13, 0.17, and 0.19) to determine the skill level of solvers and used the Flesch–Kincaid Grade Level to measure the readability of briefs, then we reestimated the path model. The results (see Appendix B) are highly similar with those in Table 2–2.

Second, in Section 2.4.1, we estimated the three equations simultaneously as a path model. To check the robustness of the path analysis estimates, we also estimated these equations separately. Again, we use negative binominal regression to model the numbers of high-skilled and low-skilled solvers and zero-inflated negative binominal regression to model the number of high-quality solutions. We use five thresholds (0.11, 0.13, 0.15, 0.17, and 0.19) to define the skill level of solvers, and the Flesch Reading Ease score and the Flesch–Kincaid Grade Level to measure readability. We again find that the estimates (for the empirical results, see Appendix D) are highly similar to their counterparts in the path analysis shown in Appendix B.

Third, the combined effects of readability and brief length on the number of high-quality solutions shown in Figure 2-4 are empirically derived from the results of the path analysis, which includes the numbers of high-skilled and low-skilled solvers as mediators. In the robustness check, we conduct a simple zero-inflated negative binominal regression to directly relate the number of high-quality solutions to readability and brief length, while excluding the numbers of high-skilled and low-skilled solvers. We present these results in Appendix E. Again, the effects of readability and brief length are positive and significant. We also determine elasticities and marginal effects based on this simple regression and compare them with their counterparts derived from the path analysis (see the figures in Appendix F). The magnitudes of the elasticities and marginal effects based on the simple zero-inflated negative binominal regression are almost the same as their counterparts based on the path analysis.

Fourth, we checked the model specification for the number of high-quality solutions. In the model specification shown previously, we assume brief length to have a linear effect on the number of high-quality solutions, and the results show that contests with a longer brief receive more high-quality solutions. However, if the brief is too long, it might contain irrelevant information that does not help solvers create high-quality solutions but rather wastes their mental resources. Thus, there might be a nonlinear effect of brief length on contest performance. To test for this nonlinear effect, we include the square term of brief length in the model for the number of high-quality solutions. The results (see the table in Appendix G) show that the square term of brief length is negative and significant. It seems that the nonlinear effect of brief length holds. However, when we draw its marginal effect (see Appendix H), we find that for almost all the sample data, the relationship between brief length and contest performance is positive, and only for very high values of brief length this relationship becomes negative. Thus, we conclude that the significance of the square term of brief length is mainly caused by a few extreme values. Compared with the nonlinear effect of brief length, we find the linear effect to be more robust. To conclude, the results of the path analysis and the hypotheses testing are robust to various changes to the analysis approach.

2.5 Discussions & Implications

Innovation contests are a promising mechanism for improving innovation by harnessing the expertise, creativity, and efforts of individuals external to the firm (Boudreau & Lakhani, 2013). A contest starts with a seeker formulating and articulating the innovation challenge and the nature of the solution that is being sought. From the seeker's perspective, solvers should be well motivated and informed by the brief that describes the innovation problem. Studies in economics, organizational behavior, and psychology provide various suggestions to improve contest design and boost contest performance (Adamczyk et al., 2012). However, few of these studies focus on the effect of the contest brief on contest performance. Although briefs are extensively studied in design research (Hey et al., 2007; Paton & Dorst, 2011; Ryd, 2004), much less is known about their function and relevance in innovation contests. Many online platforms for innovation contests suggest that seekers develop detailed briefs to improve contest performance, but the mechanism underlying this positive effect had been neither detailed nor tested. The current study fills this research gap by developing a framework to outline how contest brief characteristics, namely readability and length, affect contest performance directly and indirectly, and by testing this framework with data from a large number of real innovation contests.

Our results clearly show the importance of the contest brief. Contest brief characteristics both directly and indirectly influence contest performance. We detail five main findings. First, both brief readability and brief length have direct and positive effects on contest performance. The more readable a brief is and the more words it contains, the more high-quality solutions a contest receives. Second, both brief characteristics also indirectly influence contest performance because they affect the numbers of high-skilled and low-skilled solvers that a contest attracts. Briefs that are easier to read attract fewer high-skilled solvers and more low-skilled solvers. Longer briefs tend to attract fewer low-skilled solvers (the effect on high-skilled solvers is not significant). Third, the combined effects of brief readability and brief length on contest performance are positive. Although some of the indirect effects are negative, the combined effects, which include both the direct effect and all indirect effects, are positive for both brief characteristics. Fourth, the combined effects are not constant for all levels of readability and brief length. They increase with higher levels of readability and with a higher numbers of words in the contest brief. Fifth, high-quality solutions are submitted by both high-skilled solvers and low-skilled solvers, though we find a significantly larger effect for high-skilled solvers.

2.5.1 Contributions to literature

Taken together, our findings make several key contributions to the growing literature on innovation contests. First, the direct and indirect effects of contest briefs provide clear evidence that contest briefs affect contest performance. Previous innovation contest research has provided insights into how awards (Terwiesch & Xu, 2008), number of solvers (Boudreau et al., 2011), feedback (Ederer, 2010), and cultural factors (Bockstedt et al., 2015) affect contest performance. However, little is known about whether and how contest briefs do so. We focused on two major aspects of the writing style, readability and length, and find convincing empirical evidence that both brief characteristics directly and indirectly influence contest performance. More readable and longer briefs result in more high-quality solutions; the indirect effect is determined by the effects on the numbers of high-skilled and low-skilled solvers. By testing both direct and indirect effects, we are able to show not only that both brief characteristics matter but also how they affect contest performance. The sometimes negative indirect effects show that unexpected effects may be found when researchers focus on intermediate contest performance measures, such as the number of solvers a contest attracts, instead of on ultimate contest performance in the form of high-quality solutions. Nevertheless, for both readability and brief length, we find that the combined effect is consistently positive.

Second, innovation contest literature uses motivation theory to explain and predict solver behavior. Most studies focus on extrinsic motivation (Liu et al., 2014; Terwiesch & Xu, 2008; Toubia, 2006; Yildirim, 2005). The effects of contest briefs on the number of solvers suggest that content design characteristics, such as the brief's writing style, can intrinsically motivate solvers to join a contest. A distinct example is when high-skilled solvers enter a contest with a less readable brief, which provides them with a high-level challenge that matches their high-level skills. Our findings suggest that the contest brief can help solvers experience pleasure and satisfaction inherent in the activity and/or derive a sense of accomplishment that motivates them to join a contest, which ultimately improves contest performance.

Third, the effects of high-skilled and low-skilled solvers on the contest performance show that high-quality solutions can originate from both high-skilled and low-skilled solvers, which suggests a positive relationship between the total number of solvers and the number of high-quality solutions. This pattern echoes the parallel path effect revealed in previous research (Boudreau et al., 2011; Terwiesch & Xu, 2008). According to this effect, as the number of solvers increases and as more solvers search solutions for an innovation challenge, the likelihood of finding high-quality solutions increases. The parallel path effect suggests that both high-skilled and low-skilled solvers can be the source of high-quality solutions. Our study provides supportive evidence, but it also shows that the positive effect of the number of high-skilled solvers is significantly greater than the effect of the number of low-skilled solvers.

Fourth, the combined effects of contest briefs suggest that contest performance in terms of the number of high-quality solutions can benefit from easy-to-read and long briefs. Both findings are consistent with the rationale of the dual pathway to creativity model (Baas, Roskes, Sligte, Nijstad, & De Dreu, 2013). According to this model, creative ideas can be generated through both flexibility and persistence pathways. The persistence pathway refers to people investing their cognitive resources and systematically focusing attention and effort on the task at hand (Baas et al., 2013; De Dreu, Baas, & Nijstad, 2008; Nijstad, De Dreu, Rietzschel, & Baas, 2010). Highly informative briefs, which are long and readable, enable solvers to acquire and process detailed information about the specifics of an innovation project, thereby facilitating solvers' ability to develop creative, high-quality solutions through a persistence pathway.

Fifth, our study suggests that insights from web communication studies can be extended to innovation contest research. We find evidence that how the content of a contest is presented on the web influences the behavior of solvers and contest performance. The hypotheses that link web page complexity to solver behavior were based on theories and mechanisms from web communication studies. Our confirming evidence suggests that this related research can be applied to improve our understanding of the process and effects of online innovation contests further.

2.5.2 Managerial implications

This study provides several managerial implications for seekers. First, seekers should realize that the writing style of a contest brief affects potential solvers and, ultimately, contest performance. Seekers can increase the likelihood of attracting solvers of a certain skill level by developing a brief with a specific writing style. If organizers want to attract high-skilled solvers, they should develop briefs written in a more complex, technical style, which is less readable. If they want to attract more low-skilled solvers ("the crowd"), briefs should be shorter and more readable. If their main focus is on receiving high-quality solutions, a longer and more readable brief seems to be a wise choice. Second, we find evidence that both high-skilled and low-skilled solvers can submit high-quality solutions, which suggests two possible strategies for seekers to attract solvers. One is by relying on high-skilled solvers. Compared with low-skilled solvers, high-skilled solvers are more likely to submit high-quality solutions. Thus, by focusing on attracting high-skilled solvers, seekers can increase the likelihood of receiving high-quality solutions without having to invest much effort interacting with a large number of solvers. However, because the solutions are developed by fewer solvers, the seeker may not benefit from the diversity of solvers. The other strategy would be to rely on low-skilled solvers, by developing more readable and shorter contest briefs. As a reward, seekers will receive more diversified and high-quality solutions. The downside could be that interacting with a large group of low-skilled solvers may require more effort on the part of the seeker. Each strategy has its own advantages and disadvantages, and seekers can choose one based on their preferences.

2.5.3 Limitations and opportunities for further research

We should also mention a few limitations of our study. One limitation results from the way we operationalized brief styles. In this study, we focus on relatively simple and commonly used characteristics: readability and length. Both characteristics are explicit and concrete to seekers, and seekers can easily develop different briefs with different levels of readability and length. However, with the development of text mining, subtler dimensions of brief styles become available for researchers. Studying these dimensions may further enrich our understanding of the function of briefs in innovation contests. Another potential limitation is the way we classify solvers into high-skilled and low-skilled categories. Although the classification simplifies the conceptual framework, and the robustness checks show that the classification does not affect our findings, it limits our ability to depict precisely how solvers with different skill levels respond to briefs written in different styles. Additional studies might apply other measures to define solvers' skill level and use more advanced methods (e.g., quantile regression) to study this relationship. Finally, this study shows that high-skilled and low-skilled solvers respond differently to briefs and contest design elements (awards, contest duration, see Table 2–2). Boudreau et al. (2016) found that solvers with different skill levels respond differently to adding new solvers within a contest. Based on such findings, future studies can further explore the effect (and underlying reasons) of various skill levels of solvers on contest performance, as well as the effect of contest design elements on the attraction of and subsequent performance of various types of solvers.

To conclude, this study provides clear evidence that the brief—the first and often sole source of contest information for solvers—influences contest performance directly and indirectly. As one of the first to focus on this seemingly obvious but often-overlooked instrument, this study provides useful guidelines for how to improve contest performance and is a next step in understanding the effectiveness of online innovation contests.

3 Innovation Contest Performance: Uncertainty Moderating the Effect of Diversity[10]

Abstract: Innovation contests posted on global platforms can attract a wide range of solvers with quite different backgrounds. However, it is unclear whether such a diversity of solvers helps or hurts innovation contest performance. We uncover the effect of diversity in two steps: First, drawing on diversity literature, we hypothesize an inverted U-shape relationship between the diversity of solvers within a contest and contest performance. Second, we assume that the way a seeker has formulated the contest brief may affect the inverted U-shape relationship. A contest brief can be formulated more or less certain by using auxiliary verbs (e.g., could, would) and/or adverbs (e.g., definitely, maybe). Drawing on literature of uncertainty reduction theory, we propose that the uncertainty level of the contest brief moderates the inverted U-shape relationship between the diversity and the contest performance. We test the hypotheses with a dataset from a major global online innovation contest platform, containing 8,366 contests. The diversity of solvers is conceptualized based on variation in their expertise areas, country of residence, and experience. Contest performance is measured by the number of high-quality solutions submitted to a contest, while the uncertainty level of the contest brief is measured by the grammatical uncertainty. Empirical results confirm the proposed effects, namely: 1) there is an inverted U-shape relationship between the diversity measures and contest performance, 2) contests with more certain briefs tend to have better performance, and 3) the uncertainty level of the brief moderates the curvilinear relationships between diversity and contest performance in such a way that as the brief becomes more uncertain, the inverted U-shape shifts horizontally from a smaller to a larger value of the diversity measures. Theoretical and practical implications are discussed.

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[10] This Chapter is based on the working paper Feng Hu, Tammo Bijmolt, Eelko Huizingh. *Diversity of Solver Group, Uncertainty Level of Brief, and Performance of Innovation Contest*. Groningen, The Netherlands: University of Groningen. DOI: 10.13140/RG.2.2.20092.74886

3.1 Introduction

With the rapid development of the Internet, it has become feasible and economical for firms to make use of external sources of innovation ideas. Innovation activities, originally being mostly internal processes, have been changing (Billington & Davidson, 2013). A clear example of this development is the online innovation contest (Adamczyk et al., 2012). At the start of an innovation contest, the seeker formulates a contest brief including the description of the project, and the requirements for solutions, and posts this document either on its own website or on a third party platform for innovation contests. During the competition, the seeker can interact with solvers by commenting and/or rating solutions, while solvers can also learn from each other by checking solutions submitted by other solvers. When the contest is over, the seeker selects one or more high-quality solutions to award.

An innovation contest attracts solvers who are interested in the topic and think to be able to provide solutions to the seeker. Compared to a firm's employees, innovation contests offer access to a more diversified workforce (Daniel, Agarwal, & Stewart, 2013). Solvers may vary in their background, expertise, and experience. Take the country of residence for example, many well-known online platforms for innovation contests, such as Innocentive (www.innocentive.com), Logomyway (www.logomyway.com), and Topcoder (www.topcoder.com), claim to have worldwide solvers. Generally speaking, diversity refers to a characteristic of social grouping that reflects the degree to which objective or subjective differences exist between group members (van Knippenberg & Schippers, 2007). It has an antonym, *concentration*, and a near synonym, *variety* (Mcdonald & Dimmick, 2003). In contests hosted in such global online platforms, solvers will originate from many different countries. Solvers in a contest can differ in terms of demographics, such as gender and age, or functional aspects, such as their areas of expertise, and their experience with similar problems. Hence, solvers in a contest can feature diversity on multiple dimensions.

The other core concept of this study is uncertainty. In task contexts, uncertainty can be defined in the light of repetitiveness and openness (Hirst, 1981). Repetitiveness refers to the frequency with which the focal task is performed, and the openness refers to the extent to which the task is influenced by events or factors external to the focal task. Tasks that are non-repetitive and open to factors outside are high uncertainty tasks (Hirst, 1987).

As solvers can observe and learn from solutions developed by others, the level of diversity in a contest may affect contest performance. Such a suggestion is in line with diversity studies that have shown that diversity in groups affects performance (van Knippenberg et al., 2004; van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998). Literature reviews focusing on work group diversity identify two research traditions that diversity research has largely been guided by: the social categorization perspective and the information/decision-making perspective (van Knippenberg et al., 2004; van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998). The former holds that diversity of group members engenders the classification of in-group and out-group. People tend to like and trust in-group members more than out-group members (also labeled as “intergroup bias”) (Brewer, 1979), which may disrupt the group process and have a negative effect on the group performance (Jehn, Northcraft, & Neale, 1999; Simons, Pelled, & Smith, 1999). The information/decision-making perspective, on the other hand, predicts that diverse groups have a broader range of knowledge, and have different opinions and perspectives on the task. Group members can invest efforts to exploit such broader knowledge and reconcile different perspectives, which results in more creative solutions (Ancona & Caldwell, 1992; Bantel & Jackson, 1989; De Dreu & West, 2001).

Insights about the effects of diversity derived from studies on work groups can help us understand the effects of diversity in innovation contests. However, innovation contests feature three unique characteristics, which may impact the effects of diversity. First, computer-mediated interaction in innovation contests may suppress the social categorization perspective, but let the information/decision-making perspective untouched. Solvers in innovation contests are usually geographically and hierarchically decentralized, physically and cognitively independent. They read the contest brief, may check solutions developed by other solvers, and submit their own solutions to the contest online. Thus, innovation contests involve computer-mediated interaction. Studies show that computer-mediated interaction can remove cues of social categorizations (Sproull & Kiesler, 1986), and lower the transformation from social categorization to intergroup bias (Bhappu, Griffith, & Northcraft, 1997). Nevertheless, in innovation contests, solvers can still learn from each other by checking each other's solutions. Therefore, we conjecture that the effect of diversity in online innovation contests should be positive, because a computer-mediated design largely removes the effects of intergroup bias and leaves the positive effects rooted at exploiting such a broader knowledge or more diverse perspectives of solvers within contests.

Second, the positive effect of diversity on the contest performance may be only derived up to a certain level of diversity. Innovation contests are mostly organized online, they may have more diverse solver groups[11] than traditional organizations. As we reasoned above, contest performance may be benefit from the diversity of solver groups, just as the information/decision-making perspective predicts. However, as the diversity of solver groups increase, it becomes more likely that solvers within the same contests share less common frame of reference that helps them to understand the solutions developed by other solvers. Less understanding with one another will further make solvers less inspired by solutions developed by others, which is detrimental to the group performance (van Knippenberg et al., 2004; van Knippenberg & Schippers, 2007). Thus, when the diversity of solver groups becomes too high, the effect of diversity will be negative.

Third, the nonlinear effect of diversity on the contest performance reasoned above may be not the same in any situation, but contingent on some characteristics of innovation contests. An innovation contest is accompanied by a contest brief, which serves as a primary information source for solvers to develop solutions. One characteristic of briefs that the seekers determine is the uncertainty expressed by using auxiliary verbs (e.g., could, would) and/or adverbs (e.g., definitely, maybe). By checking briefs with

[11] solvers who join and submit solutions in a contest form a solver group of this contest

different levels of uncertainty, the solvers may perceive different levels of task uncertainty. Information seeking literature has shown that task characteristics such as task complexity or task uncertainty influence the information seeking behaviors of individuals (Vakkari, 1998). They will seek information to reduce the uncertainty (Kramer, 1999). Thus, information, which may be overlooked by the individuals in situations with certainty, will be proactively searched and processed in situations with uncertainty. Following the predictions of information/decision-making perspective (van Knippenberg et al., 2004), a high level of diversity may be detrimental to the contest performance in contests with less uncertain briefs, but may enhance the contest performance in contests with more uncertain briefs. Thus, the relationship between the diversity and the contest performance may be moderated by the uncertainty level of contest briefs.

In sum, previous studies derive many insights about the effect of diversity on group performance, and those insights provide us a foundation on which we unfold the effect of diversity in the setting of innovation contests. However, because of the three characteristics of innovation contests discussed above, the effect of diversity in innovation contests may be different from the effect in former studies. The research question of the focal paper is what is the effect of diversity of solver groups on the contest performance. The answer to this question both contributes to diversity theory for innovation contests, and helps managers to cope with the issue of diversity when organizing innovation contests. To the best of our knowledge, no study has systematically checked the nonlinear effect of diversity, and the moderating effect of uncertainty on diversity in innovation contests.

This paper fills this research gap by conducting empirical research to determine the relationship between the diversity of solvers within contests and the contest performance, and the moderating effect of the uncertainty level of contest briefs on this relationship. Diversity is captured in terms of the differences of solvers in their expertise areas, country of residence, and experience. Contest performance is measured by the number of high-quality solutions within contests. We conceptualize the uncertainty of contest briefs as grammatical uncertainty by which writers or speakers use auxiliary verbs (e.g., could, would) and/or adverbs (e.g., definitely, maybe) to express uncertainty (Rubin, 2010). We derive the data from a well-known global online innovation contest platform for logo design projects. The database contains 8,366 contests in which 19,849 solvers submit 916,545 solutions, and 153,598 of these solutions are scored as high-quality solutions by the seekers. The empirical results show that 1) diversity measures derived from expertise areas, country of residence, and experience have an inverted U-shape relationship with the number of high-quality solutions, 2) a contest with a less uncertain brief will receive more high-quality solutions than with a more uncertain brief, and 3) the uncertainty level of contest briefs moderates the inverted U-shape relationship between diversity and contest performance in such a way that as the brief becomes uncertain, the inverted U-shape shifts horizontally from a smaller to a larger value of the diversity measures.

We organize the reminder of this paper in the following way. Section 3.2 reviews the literature and develops corresponding hypotheses. Section 3.3 details the data and estimation strategies. Section 3.4 reports the empirical results. The discussions and managerial implications are shown in section 3.5.

3.2 Literature & Hypotheses

3.2.1 Diversity of solver group and contest performance

An innovation contest, which is posted on an open platform designed for seekers and solvers worldwide, may attract solvers with quite different areas of expertise, from different countries, and/or with different experience. The information/decision-making perspective assumes that a group of solvers with a higher level of diversity possesses a broader range of distinct knowledge, and has different perspectives on the project at hand (van Knippenberg et al., 2004). During the contest, a solver develops and submits solutions that are visible to the seeker and to other solvers. Different solvers develop different solutions, which contain their developers' knowledge, and understanding on the task and/or solutions. By mutually checking solutions, solvers may get inspired by knowledge and understanding of their competitors, which can help them to polish their own ideas and submit better solutions. Furthermore, the seeker can interact with solvers by commenting on solutions. By doing this, the seeker acts as an information hub, which speeds up the exchange of different perspectives and knowledge among solvers. Therefore, by sharing their solutions with other solvers and interacting with the seeker, solvers in a contest can exchange, process, and integrate diverse information and perspectives. Solvers who are exposed to diverse information and perspectives are more likely to develop innovative or creative ideas (Ancona & Caldwell, 1992; Bantel & Jackson, 1989; De Dreu & West, 2001). Therefore, as the diversity of a solver group increases, a contest will receive more high-quality solutions.

To benefit from the diversity of information and perspectives, individuals within groups should understand and integrate contributions of others. However, as the diversity of individuals increases, they share less common knowledge, background, and/or expertise, which undermines the base on which they precisely assess the contributions of others (van Knippenberg & Schippers, 2007). Consistent with this proposition, laboratory studies suggest that group discussions tend to overlook information that does not hold in common before discussion, or information that does not support existent preference of group members (Stasser & Titus, 1985). A field study revealed that as education diversity increases, the range and the depth of information used in the group will increase up to a point, and then decrease thereafter (Dahlin, Weingart, & Hinds, 2005). Therefore, we conjecture that when the diversity of solvers within contests increases beyond a certain level, solvers will have less common knowledge. They may find knowledge and perspectives in solutions developed by other solvers to be less relevant for their understanding of the project. Following the rationale of the Elaboration Likelihood Model, less personal relevant information will result in solvers being less motivated to engage in elaboration on this information (O'Keefe, 2008; Petty & Cacioppo, 1986). Therefore, the group of solvers benefits less from the diversity and may develop fewer high-quality solutions. In sum, the information/decision-making perspective predicts an inverted U-shape relationship between the diversity of solvers within contests and the contest performance in terms of the number of high-quality solutions. We formulate the following hypothesis to conclude these arguments:

HYPOTHESIS 1. *There is an inverted U-shape relationship between the diversity of solvers within a contest and contest performance.*

3.2.2 Uncertainty level of brief and contest performance

Besides the effect of diversity, the contest brief may also influence the contest performance. Before we elaborate on its effect, we first explain what the contest brief is, and how it can directly influence the contest performance.

When organizing an innovation contest, the seeker formulates a text to clarify the project goal, a ranking of relevant project features, the problem scope, solution scope and resource constraints, and the evaluation criteria. Such a text is called a contest brief. A contest brief is a vital source of information to solvers for finding possible directions for high-quality solutions. The characteristics of brief are expected to affect solvers processing of its information, which in turn, influences the likelihood of solvers developing high-quality solutions.

When a seeker develops a brief, he/she can use auxiliary verbs (e.g., could, would) and/or adverbs (e.g., definitely, maybe) to express uncertainty. In linguistics and natural language processing, such uncertainty refers to a linguistic expression of the likelihood that a propositional content in the texts is true (Nuyts, 2001). For example, “It might rain” is uncertain, whereas “It rains” is certain. A text can be classified into different level of uncertainty by identifying and coding specific auxiliary verbs and adverbs (Rubin, 2010). Contest briefs, which are formulated by seekers, can also be categorized as high or low uncertain texts. We illustrate this by means of segments from two briefs, one being certain (Brief 1) and one being uncertain (Brief 2) in writing style:

> ***Brief 1:*** *……This project is very open. I'd like a logo for a yacht. The logo could be classy or fun. I don't really have a specific idea that I am looking for. I really just want to get some creative ideas and then provide*

feedback as the concepts start coming in…….

Brief 2: *……Synaxial is a patent-based startup that focuses a very few dental surgery material that will be available online for medical professional, hospitals and clinics. The Logo has to show evoke following terms: dental, medical, professionalism, high tech (eventually)……*

Thus, a seeker can express uncertainty about the contest project by using such auxiliary verbs and adverbs, and such linguistic clues are processed by the solvers to determine what exactly the project entails and what requirements solutions need to fulfill in order to be appreciated by the seeker. The concept that is most related to uncertainty level of brief is task uncertainty, which is defined as a lack of predictability associated with inputs, processes, and outputs of the broader technical system within the work that is performed (Cordery, Morrison, Wright, & Wall, 2010; Griffin, Neal, & Parker, 2007). Typically, research and development projects feature high levels of task uncertainty (Katz & Tushman, 1979). After investigating 45 R&D project groups, Dailey (1978) found that increases in task certainty are associated with higher innovativeness and more contributions to the field of knowledge. A field study in software development projects also found that task certainty is positively related to development product quality (Rai & Al-Hindi, 2000). Consistent with this empirical evidence, we conjecture that if the brief is more certain, solvers have a clearer understanding of the project goal and/or the solution requirements. They can concentrate on finding ways to develop high-quality solutions, and do not have to spend much time on interpreting or guessing about the preferences of the seeker. Thus, in a contest with a more certain brief, solvers will be more likely to develop high-quality solutions. Based on this, we propose the following hypothesis:

HYPOTHESIS 2. *Innovation contests with more certain briefs will have better contest performance than those with more uncertain briefs.*

3.2.3 Moderating effect of uncertainty level of brief

If a seeker develops an uncertain brief by using specific auxiliary verbs and/or adverbs, the information about the project is less clear to the solvers, leaves more room for interpretation, and solvers may perceive the task as more uncertain. Individuals who experience uncertainty are motivated to seek information to reduce uncertainty (Kramer, 1999). Consistent with these points, empirical studies have revealed that a task with higher level of uncertainty renders a deeper and wider of information search and use (Byström & Järvelin, 1995; Guo, 2011), and more frequent use of other information sources (O'Reilly, 1982). Therefore, following uncertainty reduction theory, solvers will look for information to reduce their uncertainty. Solutions developed by other solvers are an important and obvious alternative source for the focal solver to search information. The submitted solutions reflect other solvers' understanding of the brief, the project, and the required solutions. Checking solutions developed by other solvers can help the focal solver to lower the uncertainty due to the brief. Therefore, the variety of knowledge and perspectives embedded in solutions by other solvers may be helpful for the focal solver if the brief is uncertain, whereas these are a less important source of information if the brief is quite clear.

As we hypothesized above, there is an inverted U-shape relationship between the diversity of solvers within a contest and contest performance, and it is the elaboration of the diverse knowledge and perspective embedded in solutions that underlies the direction of the effect of diversity (van Knippenberg et al., 2004; van Knippenberg & Schippers, 2007). When solvers join a contest with a more uncertain brief, uncertainty reduction theory predicts that they will proactively search information to reduce uncertainty. In this case, they may turn to solutions developed by other solvers. Therefore, the diverse knowledge and various perspectives embedded in solutions by other solvers are more likely to be searched, investigated, processed, and/or integrated in case of an uncertain brief. According to the information/decision-making perspective, this results in the positive effect of diversity on contest performance. Thus, the uncertainty introduced by the contest brief will enhance the positive effect of diversity, and push the inverted U-shape relationship from a smaller value to a larger value of the diversity measures. Thus, we formulate the third hypothesis:

HYPOTHESIS 3. *The uncertainty level of a contest brief moderates the inverted U-shape relationship between diversity and contest performance in such a way that as the brief becomes more uncertain, the inverted U-shape shifts horizontally from a smaller to a larger value of the diversity measures.*

3.3 Data & Methods

3.3.1 Innovation contests process

We collected data from a well-known innovation contest platform. On this website, the seeker launches a contest by posting the contest brief, providing awards, and setting the contest duration. During the contest, solvers can freely join and submit their solutions. The submitted solutions are visible to all solvers. At the same time, the seeker can comment on solutions, and assign scores to solutions, ranging from 1 to 5, indicating the extent to which the seeker appreciates a solution. When a contest is over, the seeker will award one or more solutions.

In this study, we use innovation contests for logo design projects. The database contains 8,366 contests in which 19,849 solvers submit 916,545 solutions, and 610,332 solutions are scored by the seekers. 153,598 solutions are scored with 4 or 5, and 456,734 solutions received the score of 1, 2, or 3. The data is on the contest level, and it contains the characteristics of each contest (e.g. contest duration, award). On average, each contest lasts for almost 11 days.

3.3.2 Interaction between solvers

Innovation contests in our dataset are for logo design projects, and solutions are candidate logos. Instead of using some form of verbal or written communication, solvers take note of the various interpretations and perspectives of other solvers by investigating the candidate logos that other solvers have submitted. Directly checking candidate logos allows solvers to explicitly perceive what other solvers want to convey, which facilitates solvers integrating other solvers' ideas and understandings. This is in line with what cognitive fit theory (Vessey, 1991, 2006; Vessey & Galletta, 1991) suggests. Cognitive fit theory distinguishes between two types of problem representation: symbolic (e.g., tables) and spatial (e.g., graphics). A problem-solving task can also be of two types: symbolic (e.g., retrieving a data value) and spatial (e.g., detecting the trend in the data). This theory predicts that the fit between problem representation and problem-solving task will create a consistent mental representation, which results in effective and efficient problem-solving performance. In an innovation contest for logo design the task is spatial, which implies that according to cognitive fit theory, it is easier for solvers to integrate knowledge and perspectives of other solvers by checking candidate logos developed by these others than it would have been by some form of verbal communication.

3.3.3 Measures and control variables

In this study, the diversity of a solver group is derived from the solvers' difference in expertise areas, country of residence, and experience. To calculate diversity, we use Shannon's H index (Shannon, 1948), because it is a valid flexible, and sensitive measure for this construct (Mcdonald & Dimmick, 2003). The formula of Shannon's H index is $H = -\Sigma p_i ln p_i$, where p_i is the fraction of solvers with category i. Regarding expertise, the contest platform provides solvers 15 non-exclusive areas of expertise to help them define their skill profiles[12]. Solvers can freely choose these tags in their homepage to indicate which design area(s) they are good at. We classify solvers with the same areas of expertise as a group with the same category of expertise areas. For national diversity, we classify solvers based on their country of residence. For experience diversity, we define experience of solvers in terms of the number of solutions they have submitted. We set 30 thresholds of the number of submitted solutions to define the category of experience, ranging from very low experience 0-22 and 23-45, etc. to very high experience 1282-1705 and finally 1706-5686[13]. In our sample, there are 776 combinations

[12] These areas of expertise include "logo design", "web design", "print design", "illustration", "packaging design", "mobile design", "clothing/fashion design", "product/industrial design", "naming", "taglines", "marketing copy", "web content", "SEO/SEM", "articles and books", and "business writing".

[13] To investigate the sensitivity of this definition, we also set 20 and 40 thresholds. The corresponding matching

of expertise areas, 158 categories of resident countries, and 30 categories of experience.

The uncertainty level of briefs is determined by using the python package "Pattern" (Smedt & Daelemans, 2012). This package is widely used for data mining on the web (Smedt, 2013). In this package, auxiliary verbs and adverbs that can be used to express uncertainty are labeled with specific scalar values. Then, the uncertainty level of each brief is calculated based on these scalar values and the frequency of occurrence of these auxiliary verbs and adverbs in the brief. The scale of the uncertainty level measurement is from -1 to 1, indicating the range from very certain to very uncertain.

Contest performance is conceptualized as the number of high-quality solutions the contest has received. High-quality solutions are defined as solutions with 4 or 5 score, because such solutions are most likely to be awarded by the seeker when the contest is over. 53% of awarded solutions received the maximum score of 5, and 38% received a score of 4.

All contests in our study award only one high-quality solution, and seekers will award the best solution regardless of its quality. We include the award amount (unit: $ 1,000) and contest duration (unit: day) as control variables because a primary motivation of solvers joining a contest is winning the award (Che & Gale, 2003), and a longer duration will allow more solvers to join the contest and allow them to submit more solutions.

An innovation contest can be seen as a search for solutions (Loch, Terwiesch, & Thomke, 2001; Sommer & Loch, 2004), and more submitted solutions will increase the probability of the contest receiving a high-quality solution. Therefore, in the model to determine the effect of diversity on the number of high-quality solutions, we include the number of submitted solutions as a control variable to account for this effect (Boudreau et al., 2011). Table 3–1 provides the means, standard deviations, and correlations for the dependent and independent variables.

Table 3–1 Descriptive statistics and correlations of variables

Variables	Mean	S.D.	1	2	3	4	5	6

between these thresholds and the category of experience can be found in Appendix I. Thresholds in each classifications (20, 30, and 40 thresholds) are set so as to make the number of categories between thresholds the same one another.

1. the number of high-quality solutions	18.36	19.22						
2. Uncertainty level of briefs	0.21	0.16	-0.17					
3. Expertise diversity	2.25	0.52	0.24	-0.18				
4. Country of residence diversity	2.06	0.40	0.23	-0.16	0.66			
5. Experience diversity	2.75	0.56	0.26	-0.15	0.70	0.71		
6. the number of submitted solutions	109.56	94.26	0.42	-0.23	0.57	0.55	0.57	
7. Award (unit: $ 1,000)	0.26	0.12	0.22	-0.19	0.46	0.47	0.43	0.62

Note: sample size is 8,366

3.3.4 Modeling approach

The dependent variable (the number of high-quality solutions) is a count variable. Table 3–1 shows that the variance of the number of high-quality solutions is much greater than its mean, indicating over-dispersion. Therefore, we apply negative binomial regression, instead of Poisson regression, to account for this issue. In order to minimize the multicollinearity, the uncertainty measure and the three diversity measures are centered (Aiken & West, 1991). To be specific, following studies that investigate the moderating effect on a nonlinear relationship (Lam, Huang, & Chan, 2015; Richard, Barnett, Dwyer, & Chadwick, 2004; van Der Vegt & Bunderson, 2005), we specify the following model when testing Hypothesis 3: $y = f(\beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 z + \beta_4 xz + \beta_5 x^2 z + \Sigma_{i=1}\beta_{i+5}x_i)$, where y, x, z, and x_i refer to the number of high-quality solutions, one of the three diversity measures, the measure of the uncertainty level of the brief, and other control variables, respectively.

3.4 Results

In this section, we present the results of a series of models predicting contest performance, measured by the number of high-quality solutions. The three diversity measures are highly correlated, namely around 0.70 (see Table 3–1), which causes multicollinearity if one would include them simultaneously as explanatory variables. Therefore, we test the effects of the diversity of solvers and the uncertainty of briefs on contest performance by including the diversity measures one by one (Models 1, 2, and 3). In models 4, 5, and 6, we test the moderating effect of the uncertainty of the brief and diversity on contest performance. The empirical results are reported in Table 3–2[14]. In this table, we find that the over-dispersion parameter (ln(*alpha*)) is negative and significant[15], which indicates evidence of over-dispersion of the data, and in turn, the necessity of applying the negative binominal regression. From the Cragg-Uhler R^2, we find that each model in the Table 3–2 explains about 20% of variance of the dependent variable.

Table 3–2 The effects of uncertainty of briefs and diversity of solvers on the contest performance

Dependent variable: No. high-quality solutions	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Expertise	-0.035			-0.018		
	(-1.304)			(-0.653)		
Expertise^2	-0.416^{***}			-0.420^{***}		
	(-13.461)			(-12.956)		
Country of residence		-0.056			-0.051	
		(-1.513)			(-1.359)	
Country of residence^2		-0.553^{***}			-0.548^{***}	
		(-12.800)			(-12.053)	
Experience			-0.112^{**}			-0.109^{**}
			(-3.253)			(-3.152)
Experience^2			-0.457^{***}			-0.453^{***}
			(-15.781)			(-15.099)
Uncertainty	-0.494^{***}	-0.529^{***}	-0.475^{***}	-0.680^{***}	-0.652^{***}	-0.619^{***}
	(-7.597)	(-8.159)	(-7.346)	(-9.166)	(-8.934)	(-7.892)
Expertise * Uncertainty				0.483^{***}		
				(3.376)		
Expertise^2 * Uncertainty				0.769^{***}		
				(4.664)		
Country of residence * Uncertainty					0.835^{***}	
					(4.361)	
Country of residence^2 * Uncertainty					0.879^{***}	
					(3.701)	
Experience * Uncertainty						0.540^{***}
						(3.557)
Experience^2 * Uncertainty						0.460^{**}
						(2.893)
No. submitted solutions	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}
	(25.125)	(23.693)	(20.181)	(25.640)	(24.129)	(20.329)
award (unit: $ 1,000)	-0.379^{**}	-0.359^{**}	-0.565^{***}	-0.363^{**}	-0.364^{**}	-0.587^{***}

[14] The results of experience diversity defined by 20 and 40 thresholds can be found in Appendix J. The results are almost the same as it shown in Model 3 and 6.
[15] If the data does not have the issue of over-dispersion, the value of ln(*alpha*) should be –inf.

	(-3.260)	(-3.051)	(-4.752)	(-3.134)	(-3.113)	(-4.938)
Constant	2.453***	2.455***	2.535***	2.443***	2.452***	2.534***
	(76.778)	(75.690)	(75.483)	(76.897)	(75.892)	(75.517)
Over-dispersion						
ln(*alpha*)	-0.328***	-0.316***	-0.340***	-0.331***	-0.319***	-0.342***
	(-19.293)	(-18.717)	(-19.669)	(-19.493)	(-18.899)	(-19.756)
Observations	8,366	8,366	8,366	8,366	8,366	8,366
Cragg-Uhler R^2	0.207	0.199	0.217	0.210	0.201	0.219

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.1 Main effect of diversity of solver group

Hypothesis 1 predicts an inverted U-shape relationship between the diversity measures and the contest performance in terms of the number of high-quality solutions. The empirical results in Models 1, 2, and 3 show that the square terms of diversity measures are negative and highly significant. Furthermore, the linear effects of the diversity measures are relatively small, so the top of the inverted U-shape will be around zero, the intermediate values of diversity. In Models 4, 5, and 6, where the uncertainty level of briefs and its interaction terms with the three diversity measures are included, the square terms of the diversity measures are still negative and highly significant. Based on the estimation in Models 1, 2, and 3, we draw the relationship between the diversity measures and the number of high-quality solutions in Figures 3-1, 3-2, and 3-3. In these figures, all independent variables except for the diversity measures are set to their mean values. We also add the histogram of the density of diversity measures in each figure[16]. These figures clearly depict an inverted U-shape relationship between the extent of diversity of the solvers and contest performance. Thus, Hypothesis 1 is supported.

[16] The right vertical axis in each figure shows the density of the diversity measures (the same below). Since both the diversity measures and the uncertainty level of the brief are centered, the lower limits of them are at negative values.

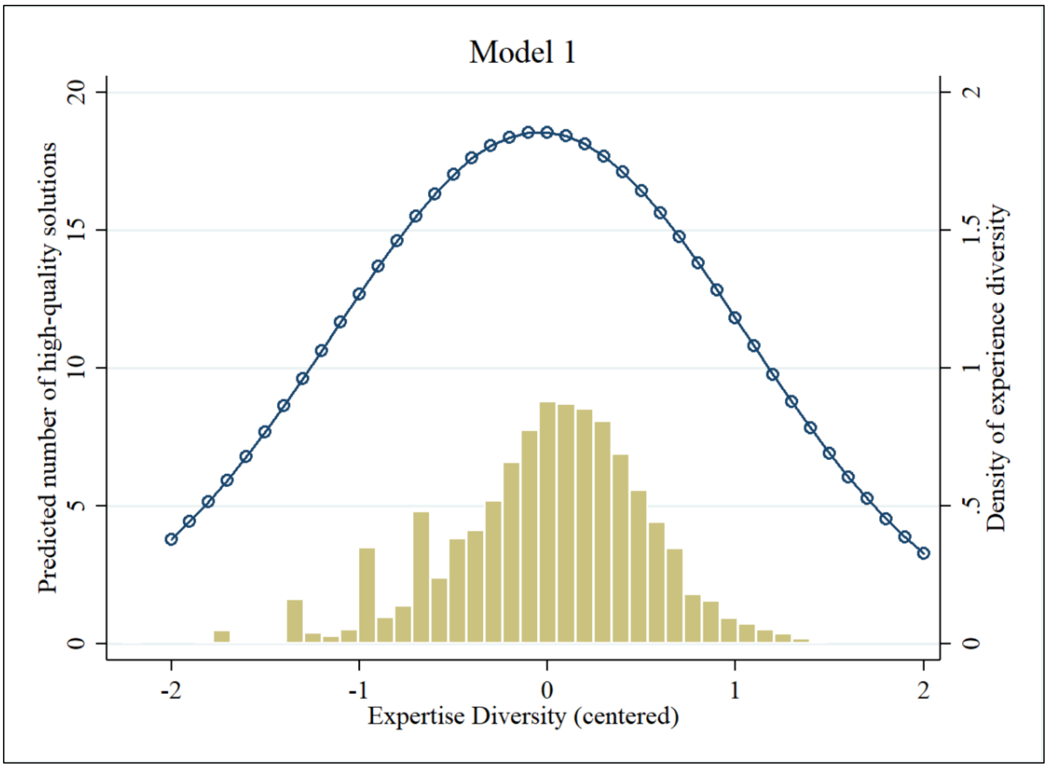

Figure 3–1 The Curvilinear effect of expertise diversity on the contest performance

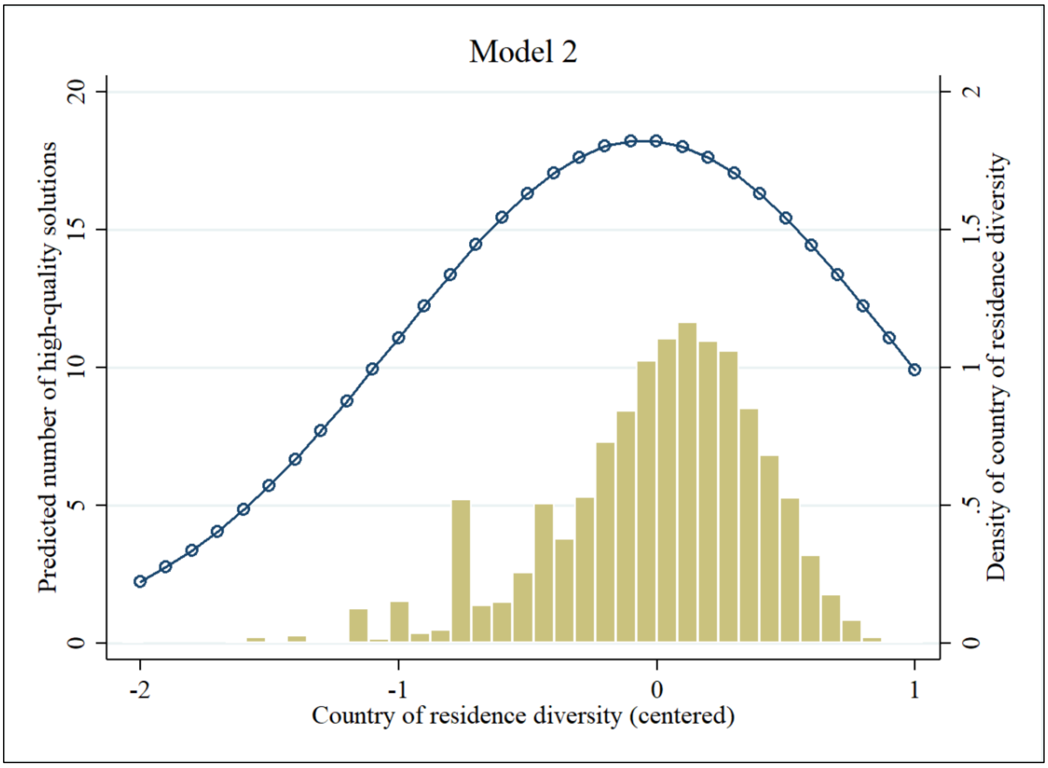

Figure 3–2 The curvilinear effect of country of residence diversity on the contest performance

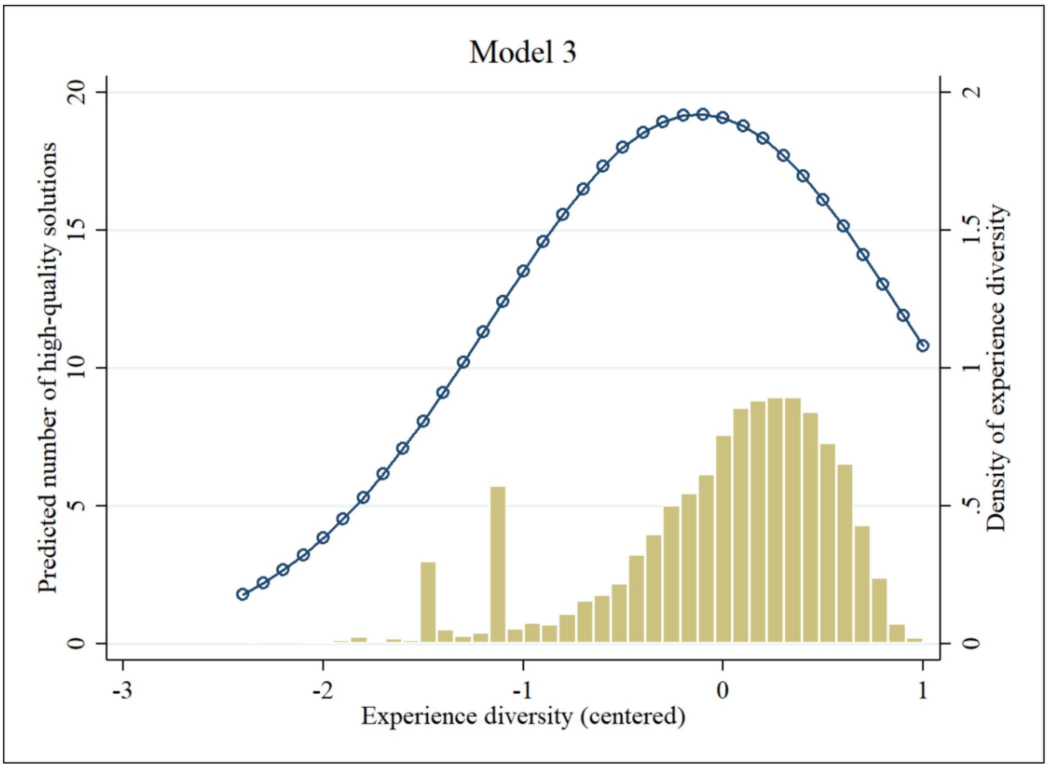

Figure 3–3 The curvilinear effect of experience diversity on the contest performance

3.4.2 Main effect of uncertainty level of contest brief

Hypothesis 2 predicts that an innovation contest with a more uncertain brief tends to have less high-quality solutions. The empirical results in Models 1 to 6 (see Table 3–2) indeed show a significant and negative relationship between the uncertainty measure and the number of high-quality solutions. Based on the results in Model 1, we draw the effect of the uncertainty measure on the contest performance in Figure 3-4[17] to illustrate the size of the effect. Within the range of observed uncertainty levels, the predicted number of high-quality solutions increases from around 15 to 23. Thus, the empirical results in Table 3–2, and the significant effect revealed in Figure 3-4 consistently support Hypothesis 2.

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[17] In this figure, independent variables except for the uncertainty level of briefs are set to their mean values.

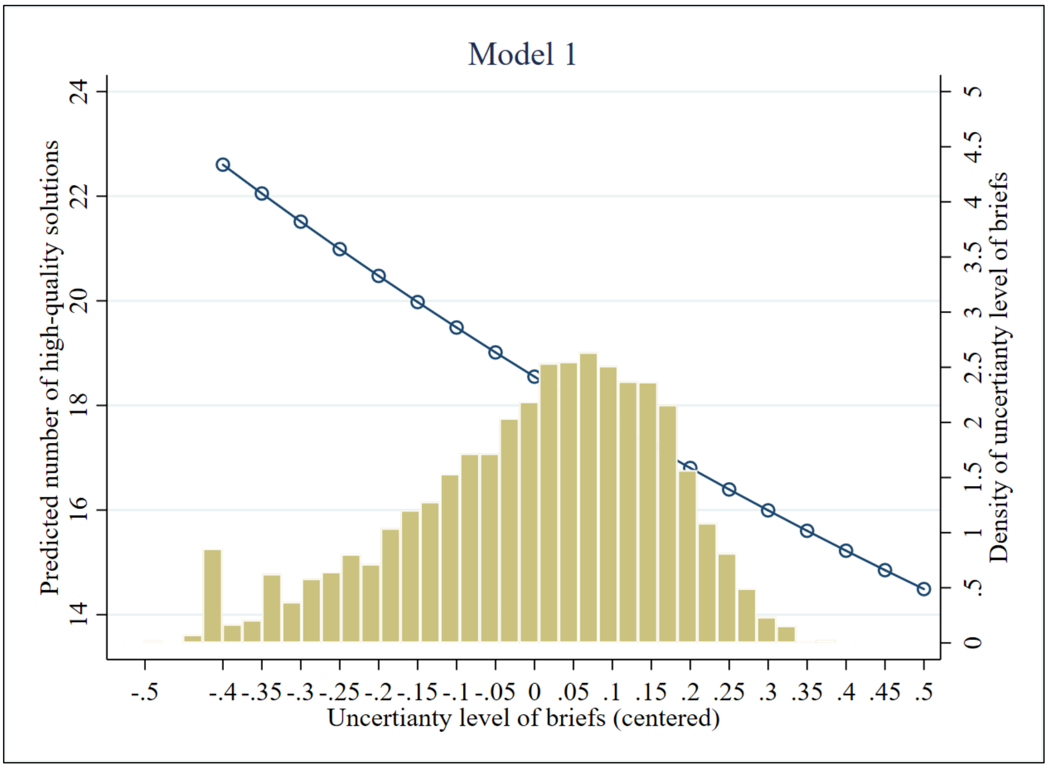

Figure 3–4 The effect of the uncertainty of briefs on the contest performance

3.4.3 Moderating effects of the uncertainty level of briefs

Hypothesis 3 predicts that the uncertainty level of the brief moderates the effect of diversity on contest performance. Results in Models 4, 5, and 6 show that the interaction terms between the uncertainty measure and the diversity measures (linear term and the square term) are all significant. To further investigate these interactions, we draw the effect of diversity on contest performance at different levels of brief uncertainty based on the results in Models 4, 5, and 6. Figures 3-5, 3-6 and 3-7[18] depict the predicted number of high-quality solutions at high and low uncertainty level of briefs, which correspond to the mean minus/plus two standard deviations of uncertainty measures. In each figure, vertical lines indicate the horizontal position of the inflection points of the inverted U-shape relationship. These graphs show that as a brief becomes less uncertain, the inflection point of the inverted U-shape relationship between diversity and contest performance shifts horizontally from a larger to a smaller value of the diversity measure.

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[18] In three figures, independent variables except for the uncertainty level of briefs and three diversity measures are set to their mean values.

Furthermore, the maximum predicted number of high-quality solutions is larger for low uncertainty than for high uncertainty contests. This reflects the main effect of brief uncertainty. Hence, the significant effects in Models 5, 6, and 7, and the patterns of the shifting inflection points shown in Figures 3-5, 3-6, and 3-7 support Hypothesis 3.

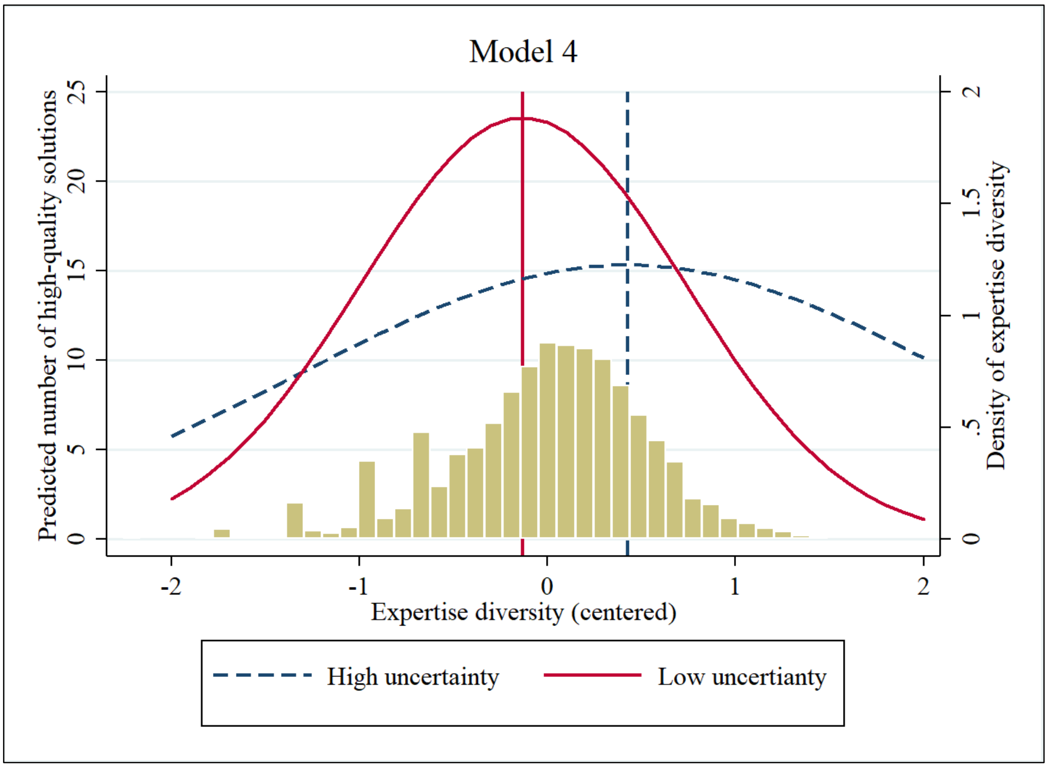

Figure 3–5 The moderating effect of uncertainty level of briefs on the relationship between the expertise diversity and the contest performance

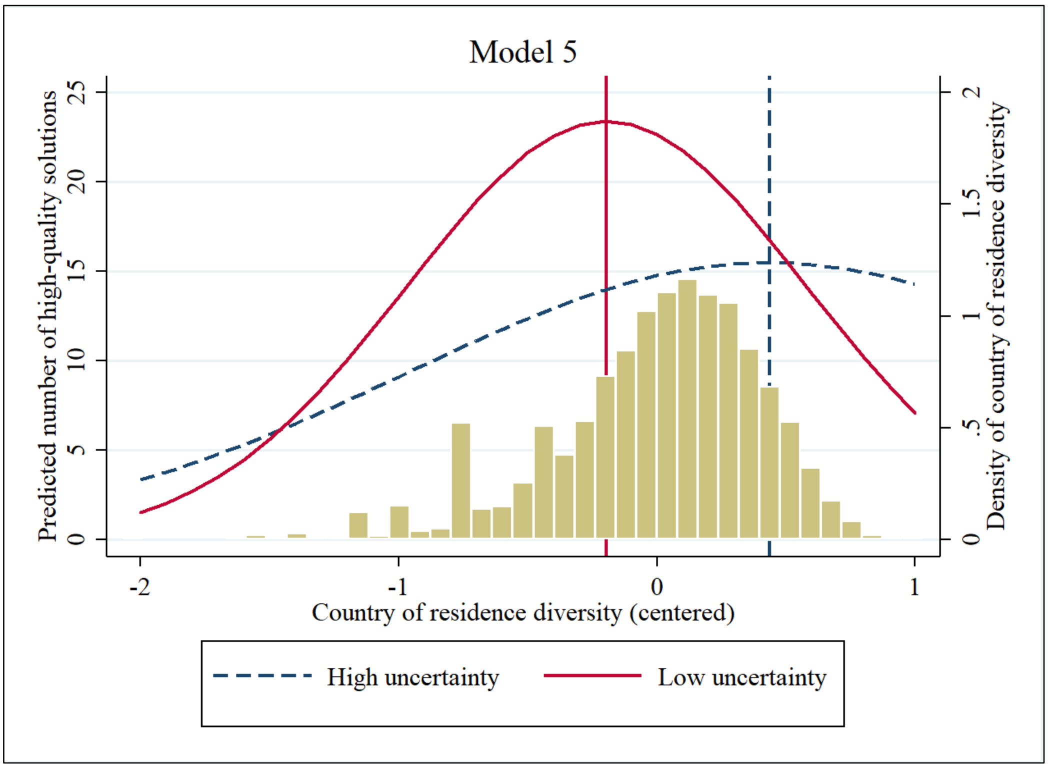

Figure 3–6 The moderating effect of uncertainty level of briefs on the relationship between the country of residence diversity and the contest performance

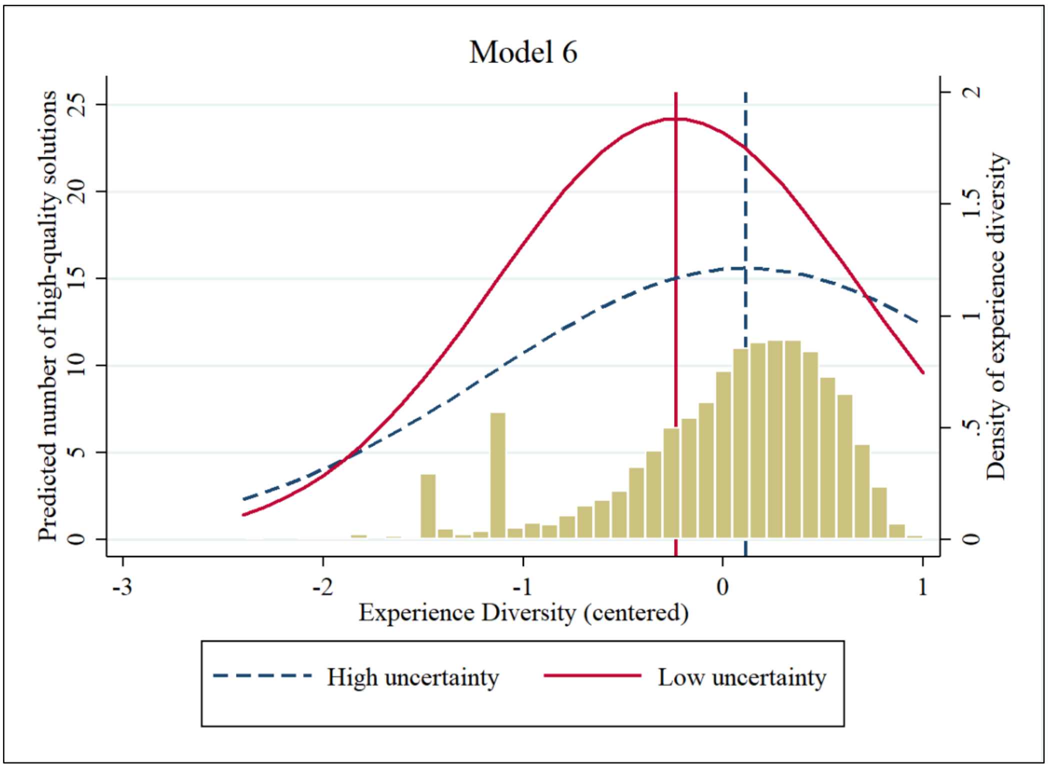

Figure 3–7 The moderating effect of uncertainty level of briefs on the relationship between the experience diversity and the contest performance

3.4.4 Effects of control variables

Besides the effects of diversity and uncertainty, we also find significant effects for some control variables. First, the coefficient of the number of submitted solutions is consistently significant and positive, implying that as contests receive more solutions, they also tend to have more high-quality solutions. Second, the effect of awards is consistently significant and negative. Higher awards in a contest may motivate solvers to submit solutions. However, it may also signal that the innovation problem is harder to solve. Thus, solvers may be less likely to develop high-quality solutions.

3.4.5 Possible relationships between uncertainty and diversity measures

As explained, project information is mainly provided by the contest brief, which may potentially affect solvers joining the contest. In other words, solvers may selectively join a contest because they like a more certain or more uncertain brief. Thus, the uncertainty level of the brief may affect the diversity of a solver group. In order to examine this, we computed the correlations between diversity measures and the uncertainty level of the brief. These correlation coefficients range from 0.15 to 0.18 (see Table 3–1), which indicates only a weak relationship (Evans, 1996). Therefore, we conclude that the uncertainty level of briefs shows little influence on the various diversity measures, and that the hypothesis testing in this study does not suffer from multicollinearity between the uncertainty level of the brief and the three diversity measures.

3.5 Summary & Implications

3.5.1 Summary

Compared with traditional innovation mechanisms, online innovation contests feature diverse solvers, which are connected through the Internet. Diversity has been heavily studied in literature of organizational behavior and human resource management (van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998). However, little is known about this topic in the field of innovation contests. To our best knowledge, no study has examined the effect of the diversity of solvers within a contest on contest performance, and how the organizer of a contest can influence the effect of diversity. This study fills this research gap by conducting an empirical study to determine the valence of this effect, and provides ways for organizers to proactively cope with the issue of diversity.

Our study represents the efforts to formally develop and test the effect of diversity in innovation contest, and it highlights the importance of exploring the nonlinearity in the relationship between the diversity and contest performance. The empirical results show that 1) it is not low or high, but a moderate level of solver diversity that corresponds with the best contest performance, 2) contests with more certain briefs tend to have better contest performance, and 3) the uncertainty level of a contest brief moderates the curvilinear relationship between diversity and contest performance in such a way that as the brief becomes more uncertain, the inverted U-shape shifts horizontally from a smaller to a larger value of the diversity measures.

3.5.2 Theoretical implications

This study has several contributions to the theories on diversity and innovation contests. First, it explicitly reveals that the diversity of solvers impacts innovation contest performance. This expands the application of diversity theory from traditional organizations in which individuals interact with each other mostly in a face-to-face way to innovation contests in which solvers use computer-mediated methods and do not directly exchange information with each other. Researchers in psychology, economy, sociology, and management science conceptualize diversity as the differences in age, education, competence, nationality, gender, and tenure of individuals, and find that diversity has both positive and negative effects on group performance (van Knippenberg et al., 2004; Williams & O'Reilly, 1998). In this study, individuals in innovation contests are connected in a computer-mediated way. The social categorization process can be largely suppressed. However, the computer-mediated interaction among solvers does not affect them investigating and integrating the diverse knowledge and/or perspectives embedded in solutions. Thus, innovation contests can benefit from the diversity of solvers. However, when diversity becomes very large, knowledge and/or perspectives embedded in solutions developed by other solvers may be perceived by the focal solver as less relevant to understanding the innovation project. It could be that the range of interpretations has become so broad that it starts confusing solvers, as a result solvers benefit less from a high level of diversity.

Second, the consistent nonlinear effects of expertise, country of residence, and experience diversity on contest performance revealed in this study suggest that the effect of diversity generalizes to a range of typologies of diversity. Some studies classify diversity into different types, and argue that the valence of its effect on group performance relates to its typology. For example, demographic diversity (e.g. gender, ethnicity) is proposed to negatively affect the group performance, while information-related diversity (e.g. education, expertise) would have a positive effect (Jehn et al., 1999; Pelled, Eisenhardt, & Xin, 1999). However, as we proposed and tested in this study, both demographic diversity (country of residence) and information-related diversity (expertise and experience) have comparable nonlinear effects on contest performance. Thus, we cannot categorize the effects of diversity simply according to their typology. Our findings seem to support the proposition that it is the elaboration of task-relevant information that underlies the positive effect of diversity on group performance (van Knippenberg et al., 2004).

Third, Figures 3-5, 3-6, and 3-7 show that the number of high-quality solutions at the inflection point increases as the brief becomes more certain. For a more certain brief the number of high quality solutions is higher at the optimum level of diversity than it is for a brief that is formulated in a less certain manner. This moderating effect can be explained by the main effect of the uncertainty level of a brief on contest performance (Hypothesis 2). It suggests that a contest benefits mostly from a more certain brief, and a moderate level of diversity. This finding echoes the dual pathway creativity model (Baas et al., 2013). This model argues that the generation of original and appropriate ideas is a function of cognitive persistence and cognitive flexibility. Individuals may achieve creative ideas by systematic, effortful, and/or in-depth exploration of only a few categories or perspectives (cognitive persistence), or by applying broad and inclusive cognitive categories through flexible switching among categories, and/or through the use of remote associations (cognitive flexibility). Individuals can use both ways at the same time (Nijstad et al., 2010). Consistent with the proposition of the dual path way creativity model, a certain brief provides solvers with clear information, which facilitates solvers relying on cognitive persistence to develop innovative ideas. A moderate diversity provides them the space of interpretations in which they can explore and exploit other perspectives. The combination of both processes, just as the results show, provides the contest with most high-quality solutions.

Fourth, following the rationale of the information/decision-making perspective, factors influencing individuals exploiting task-relevant information potentially moderate the effect of diversity on group performance. Diversity literature suggests that motivation and ability can act as antecedents of group members applying diverse information (van Knippenberg & Schippers, 2007). Consistent with such propositions, this study suggests that the uncertainty introduced by contest briefs induces the solvers proactively searching information to reduce the uncertainty, which moderates the relationship between diversity and contest performance. This study amplifies the insights about the effects of diversity on group performance, and underpins a new way of managing the diversity in work groups.

Last, this study also sheds light on the importance of the contest brief in innovation contest research. The contest brief is the main source from which solvers receive contest information, and it potentially affects the behaviors of solvers, as well as the contest performance. However, innovation contest research has not paid much attention to the contest brief yet, and the insights of how to leverage it for better contest performance are quite rare. This study addresses this gap by proposing and finding empirical evidence for the main effect of the uncertainty level of a brief on contest performance and the moderating effect of brief uncertainty on the relationship between solver diversity and contest performance. These findings will contribute to an integrative framework depicting the effects of the contest brief in future research.

3.5.3 Managerial implications

Our results have three implications for managers organizing innovation contests. First, from Figures 3-1, 3-2, and 3-3, the inverted U-shape relationship between the diversity of a solver group and contest performance implies that there is an optimal diversity level for a contest with a given brief. A moderate, rather than very low or very high, level of diversity leads to the best contest performance. This implies that it may not always be the best choice to have solvers freely joining contests ("free-entry" policy), since seekers can then not influence the diversity level of the solver group. After checking innovation contest platforms online, we find that almost all of them do not provide such an index to denote the diversity of solver groups for contests organized on it. Thus, these platforms are recommended to design such index, and make it available to the seeker. Furthermore, platforms may consider revising the "free-entry" policy, and actively promote and monitor challenges in such a way that a contest reaches and stays at a medium level of diversity. Since the magnitude of the inflection points is contingent on the type and the calculation method of diversity, we cannot approximate a single inflection point for all kinds of diversity measures in all contests. To be specific, Results in Figures 3-1, 3-2, and 3-3 indicate that the inflection points appear at almost zero of the magnitude of three diversity measures. Thus, for the innovation contest platform from which we derive the data, the seeker should proactively select solvers in terms of their diversity so as to keep the indices for expertise diversity, country of residence diversity, and experience diversity at 2.25, 2.06, and 2.75, respectively[19]. Second, the effect of the uncertainty level of a brief on contest performance (see Figure 3-4) suggests that a more certain brief is more helpful to solvers than an uncertain brief. Where possible, seekers should use proper auxiliary verbs and/or adverbs to convey certain

[19] Notice that measures of expertise diversity, country of residence diversity, and experience diversity in Figures 3-1, 3-2, and 3-3 are centered. Their mean values are 2.25, 2.06, and 2.75, respectively. Thus, diversity measures in Figures 3-1, 3-2, and 3-3 being zero means the original diversity measures being their mean values.

message to their solvers. Finally, as Hypothesis 3 predicts, the uncertainty level of brief moderates the nonlinear effect of diversity on contest performance. The inverted U-shape shifts horizontally as the brief becomes more uncertain. Due to this shifting, solvers in a contest will develop more high-quality solutions with an uncertain brief than with a certain brief when the diversity of solver groups reaches a highest level (see the very right side of Figures 3-5, 3-6, and 3-7). Thus, if the seeker expects to be confronted with a very diverse solver group, an uncertain brief will be a better choice.

3.5.4 Limitations and future research

A few limitations of our study should also be mentioned. The first is the type of diversity. Results in this study show that diversity derived from the differences of expertise areas, country of residence, and experience has the same effects on the contest performance, diversity in terms of more discernable differences such as in gender and age is not included. Future studies can further check more types of diversity and test whether and to what extent they have the same nonlinear effects. Another potential limitation is related to the uncertainty level of a contest brief. Generally speaking, uncertainty is a multidimensional concept. It can be a psychological phenomenon or an experience related to the task, or a linguistic and epistemic phenomenon in texts (Rubin, 2010). Obviously, we applied the latter one in this study. However, the former one can be a characteristic of a task, and can be measured by the number of knowledge domains from which a task draws (Boudreau et al., 2011). Future studies can further check the moderating effect of uncertainty measured by the number of knowledge domains to provide more insights of diversity effects. The third limitation is relevant to the contest design. The platform from which we have data does not allow solvers to directly interact with each other, solvers within each contest competitively develop and submit solutions to the seeker. However, previous diversity studies focused on groups in which the members directly communicate and collaborate with each other. Future studies can examine the effect of diversity in innovation contests that allow direct communication and/or collaboration among solvers. The last limitation is the contest category we use in this study. In design projects, the rules used by seekers to score solutions are relatively subjective, and solutions with diverse styles or perspectives can potentially be the awarded solutions. Thus, the performance of design contests can be affected by the diversity of solvers. However, in coding or programming projects, the quality of solutions may be less relevant to the coding styles or perspectives, but more determined by the skill level of the developers. Therefore, the (nonlinear) effect of diversity revealed in this study may be less outspoken or not even significant. Future studies can check the effect of diversity on contest performance in coding or programming projects to determine the situational contingencies of effect of diversity in innovation contests.

In conclusion, this study determines the effect of diversity of solver groups and uncertainty of the brief on contest performance. It both paves the way to a better understanding of the role of diversity in innovation contests, and provides managers with hints of how to deal with the diversity issue when searching for high-quality solutions in an innovation contest.

4 Dynamics of Solvers and High Quality Solutions in Innovation Contests[20]

Abstract: The current study extends research on open innovation contests by focusing on the process of an innovation contest. The authors predict interrelationships between the number of solvers and the numbers of low- and high-quality solutions, and they test these predictions in an empirical analysis using a unique data set of 1,789 open innovation contests for design projects. The results reveal that (1) a solver is less likely to join a contest that already has many more solvers, many high-quality solutions, and many low-quality solutions; (2) a solver is more likely to submit another high-quality solution if he or she already has submitted more high-quality solutions to the same contest; (3) a solver is less likely to submit a high-quality solution if the contest already has many solvers or many high-quality solutions developed by others; and (4) the availability of low-quality solutions, developed by either the focal solver or others, increases the probability of a focal solver submitting a high-quality solution. Organizers of open innovation contests should understand these complex relationships when they design and manage contests and aim to improve contest performance. This article details the implications of these findings for the theory and practice of innovation contests.

[20] This Chapter is based on the working paper Feng Hu, Tammo Bijmolt, Eelko Huizingh. *Dynamics of Solvers and High Quality Solutions in Open Innovation Contests.* Groningen, The Netherlands: University of Groningen. DOI: 10.13140/RG.2.2.23369.54888

4.1 Introduction

Since users can be more efficient to create innovations than product producers (Hienerth, von Hippel, & Berg Jensen, 2014), firms are increasingly shifting the dominant logic of R&D away from internal discovery toward external engagement (West et al., 2014). One popular way is by organizing innovation contests (Boudreau & Lakhani, 2013). Major companies have hosted innovation contests to generate valuable ideas, including Dell, Best Buy, BBC, CNN, BMW, and Adobe (Huang et al., 2014). Innovation contests can be conducted on company websites or on dedicated platforms hosted by third parties. Innovation projects, such as program coding (e.g., TopCoder [www.topcoder.com]) and design works (e.g., 99designs [en.99designs.nl]) can attract high-quality solutions through innovation contests on dedicated platforms. These platforms act as intermediaries between firms (also known as “seekers”) that are looking solutions and the crowd (also known as “solvers”) who provide solutions. Innovation contests are good at solving clearly defined, well-structured, and simple problems (Felin & Zenger, 2014).

A typical contest using a dedicated platform involves the following steps: A seeker formulates a brief, which describes the problem, defines the prerequisites for acceptable solutions, and communicates the award(s) being offered for the best solution(s). This brief is made available to solvers. Depending on their availability, skills, and interests, some of them will work on the problem and submit solution(s) to the platform. The platform makes these solutions available to the seeker, and the seeker scores the solutions based on their quality. High- (low-) quality solutions are those that are more (low) likely to be awarded. Solvers are typically allowed to submit multiple solutions, and they can use the scoring feedback from the seeker to polish their ideas and resubmit improved solutions. The steps of submission and feedback repeat until the contest ends at a pre-announced date. At the end of the contest, the seeker selects one or more high-quality solutions to receive an award. Contests can provide solutions efficiently and economically because (1) they induce competition among solvers, (2) the seeker pays only for the best solution(s) but not for lower-quality ones, and (3) the problem can be worked on by a large pool of qualified solvers (Terwiesch & Xu, 2008).

In response to the growing popularity of innovation contests in industry, academic literature has focused on the drivers of innovation contest performance. Existing literature suggests that awards (Terwiesch & Xu, 2008), information feedback (Aoyagi, 2010), solver ranking (Yücesan, 2013), and the number of solvers involved (Boudreau et al., 2011; Fullerton & McAfee, 1999) all affect contest performance. Most of these studies treat innovation contests as one-round competitions. They tend to overlook the competition among solvers during the process of the contest. For example, if a contest has already attracted many solvers and/or many high-quality solutions, the probability of a new solver joining the contest ($P_t(J)$) may be lower because new solvers may conclude that the probability of winning an award is lower due to strong competition. In a similar vein, the probability of a solver submitting a high-quality solution ($P_t(HQ)$) may decrease due to an increasing number of solvers and/or high-quality solutions developed by others. Furthermore, the currently available number of low-quality solutions may influence $P_t(J)$ and $P_t(HQ)$ because these solutions may signal high standards imposed by the seeker and thus convey useful feedback to solvers. Therefore, in this study, we test whether the number of solvers and the number of high-quality solutions are mutually related and that each behaves as a dynamic process: both $P_t(J)$ and $P_t(HQ)$ are functions of the currently available number of solvers and high-quality solutions (thus, the increment is a function of its stock). When designing and/or managing a contest, a seeker needs to be aware of such interrelationships among the number of solvers, the number of high-quality solutions, and the number of low-quality solutions. Some modeling studies have addressed the dynamics during competition (Aoyagi, 2010; Ederer, 2010), but their assumptions are less realistic. For example, they assume two agents to compete in contests in which each agent is allowed to submit only twice (two-round contests). However, innovation contests usually contain more than two solvers and allow solvers to submit their solutions sequentially over many rounds. To conclude, the available literature provides very limited understanding of (1) the mutual relationships between the numbers of solvers and high-quality solutions and (2) how to design and manage contests in light of this relationship.

This article seeks to fill these research gaps. We focus on the competition process among solvers during a contest and build our logic on the premise that contest performance is not determined solely by the contest design elements (e.g., awards, contest duration) determined by the seeker at the start of the contest. First, we build a conceptual framework for the relationships between solvers and high-quality solutions. Second, we conduct empirical analyses to assess these relationships. We use data on innovation contests gathered from a well-known online platform for design projects. In our data set, a total of 20,617 solvers join 1,789 innovation contests and submit 357,057 solutions; of these solutions, 11.3% are rated as high-quality solutions by the seekers. Based on the conceptual model and the nature of the data, we build generalized linear mixed models, in which we include random effects to account for heterogeneity between different contests and solvers.

Our empirical results reveal the following:

1. Solvers are less likely to join a contest that already has more solvers, more high-quality solutions, or more low-quality solutions.

2. Solvers are more likely to submit another high-quality solution if they have already submitted one or more high-quality solutions to the same contest.

3. Solvers are less likely to submit another high-quality solution if the contest already has more solvers or more high-quality solutions developed by others.

4. The availability of low-quality solutions, developed by either the focal solver or others, increases the probability of the focal solver submitting a high-quality solution.

From these empirical results, we formulate implications for managers who are running and/or designing innovation contests.

We organize the rest of this paper as follows: In Section 4.2, we build a framework to conceptualize the relationships between solvers and high-/low-quality solutions and formulate hypotheses about these relationships. In Section 4.3, we detail the empirical setting of our study and describe the data and estimation strategies. We present the empirical results in Section 4.4. In Section 4.5, we conclude with a discussion of the implications and contributions.

4.2 Conceptual Model & Hypotheses

In this section, we present our research framework to outline the dynamic processes involved in innovation contests (see Figure 4-1). This framework guides our formulation of hypotheses about the effects on the probability of a solver joining a contest at a given moment *t* (i.e., $P_t(J)$) and on the probability of a solver submitting a high-quality solution at a given moment *t* (i.e., $P_t(HQ)$).

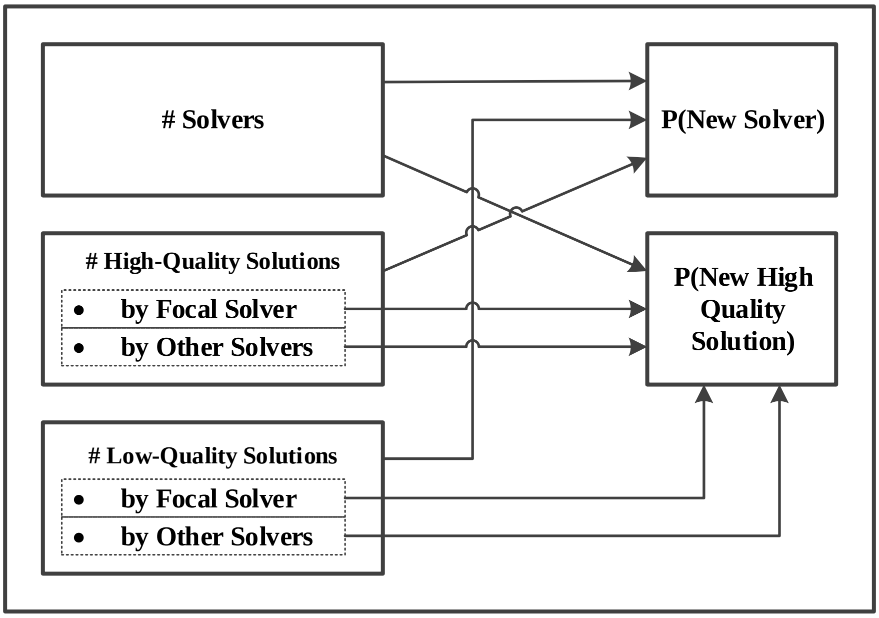

Figure 4–1 Research framework: all independent variables refer to the number of solvers (solutions) in a contest at a given point in time.

4.2.1 Effects on the probability of a new solver joining a contest

4.2.1.1 Effect of solvers

To encourage solvers to join contests and invest sufficient time and effort into formulating high-quality solutions, seekers motivate solvers by offering incentives. Such motivation includes two types: extrinsic and intrinsic (Loch et al., 2000; Vidal & Nossol, 2011; von Hippel, 2005). In this section we discuss the extrinsic part. The intrinsic part comes later. Extrinsic motivation is increased by creating an opportunity to achieve a goal, such as winning an award (Deci & Ryan, 1980). A new solver is less likely to win an award if more solvers have already joined a contest, which may lower their extrinsic motivation to join the contest, thus decreasing $P_t(J)$. In line with this argument, we formulate the following hypothesis:

HYPOTHESIS 1-1. *The current number of solvers in a contest negatively affects the probability of a new solver joining the contest*.

In contrast, more solvers in a contest might attract other solvers to the contest. Studies show that in a sequential decision situation, where each individual makes his or her decision one-by-one, individuals look at other people's previous decisions when making their own and determine whether their decisions are rational based on whether they believe former decision makers have important information that they lack. This decision rule leads to herd behavior (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). Herd behavior is a common phenomenon in social and economic situations. For example, online shoppers tend to base their purchase behavior on the volume of online word of mouth from other consumers (Rosario, Sotgiu, De Valck, & Bijmolt, 2016). Similarly, software users typically download software that has been downloaded most often by others (Hanson & Putler, 1996). Herd behavior is more likely when the decision-making setting is complex and decision makers are constrained by time and/or information availability (Shiller, 1995). In contests in which solvers can freely decide whether and when to join, a major decision for potential solvers is to determine the contest(s) in which they should invest their efforts. Solvers may think that contests with many solvers have some appeal or advantage. Following the rationale of herd behavior, more solvers in a contest may attract new solvers to join the contest, thereby increasing $P_t(J)$. Thus, we develop the following alternative hypothesis:

HYPOTHESIS 1-2. *The current number of solvers in a contest positively affects the probability of a new solver joining the contest.*

4.2.1.2 Effect of high-quality solutions

Seekers want high-quality solutions and are therefore more likely to award these solutions at the end of the contest. Thus, a large number of high-quality solutions available in the contest signals increased competition and a lower likelihood for a new solver to win the contest. In line with the reasoning above, a decrease in the probability of winning the contest undermines a new solver's extrinsic motivation, which demotivates a solver to join the contest. Thus, we propose the following hypothesis:

HYPOTHESIS 2. *The current number of high-quality solutions in a contest negatively affects the probability of a new solver joining the contest.*

4.2.1.3 Effect of low-quality solutions

A contest with many low-quality solutions signals that the seeker of the contest may have high standards and is not easily satisfied. A critical seeker is less likely to score new solutions as high quality, and thus potential solvers may infer that they are less likely to win such a contest. Again, this may decrease solvers' extrinsic motivation, which in turn lowers the probability of solvers joining the contest ($P_t(J)$). Thus, we propose the following hypothesis:

HYPOTHESIS 3. The current number of low-quality solutions in a contest negatively affects the probability of a new solver joining the contest.

4.2.2 Effects on the probability to obtaining a new high-quality solution

4.2.2.1 Effect of solvers

Solvers invest time to devise, develop and submit high-quality solutions with the hope of winning an award. However, innovation contest studies have shown that more solvers in a contest lowers the likelihood for individual solvers to win the contest, which negatively affects their motivation to improve their solutions, and ultimately downgrades the quality of solutions (Boudreau et al., 2011; Che & Gale, 2003; Fullerton

& McAfee, 1999; Konrad, 2009; Moldovanu, Sela, & Shi, 2007; Taylor, 1995; Terwiesch & Xu, 2008). Therefore, we propose the following hypothesis:

HYPOTHESIS 4. The current number of solvers in a contest negatively affects the probability of a solver submitting a high-quality solution in the contest.

4.2.2.2 Effect of high-quality and low-quality solutions by the focal solver

The high-quality and low-quality solutions in a contest can be divided into those developed by the focal solver and those developed by others. Having developed high-quality solutions will affect the probability of submitting another high-quality solution for two reasons. First, a solution scored as high quality indicates that the seeker likes and appreciates it. Such verbal praise and positive performance feedback can give solvers a sense of accomplishment and competence, which in turn increases their intrinsic motivation (Anderson, Manoogian, & Reznick, 1976; J. Cameron & Pierce, 1994; Deci, 1971, 1972; Harackiewicz, 1979). Increased intrinsic motivation positively influences the performance of individuals (Ryan & Deci, 2000). Thus, solvers with more high-quality solutions in a contest will be more motivated to submit another high-quality solution in the same contest. Second, high-quality solutions can be regarded as a source of solution requirements information for solvers. Scoring a solution as high-quality requires a good match between the solution and the subjective opinion of the seeker (Terwiesch & Xu, 2008). Thus, solutions scored as high quality by the seeker provide clues about the seeker's preferences, and a potential path forward for the solver, which facilitates the solver in developing another high-quality solution.

In contrast with the predictions of motivation and feedback theories, other mechanisms suggest a negative relationship between the current number of high-quality solutions and the probability of the same solver submitting another high-quality solution. For example, control theory suggests that people's responses to performance feedback are determined by their desire to minimize the distance between their performance and their internal goals (Taylor, Fisher, & Ilgen, 1984). When feedback indicates that they have met or exceeded an internal standard, their efforts and goals usually remain the same in subsequent tasks. If the feedback indicates that their performance has fallen behind an internal standard, they either invest more effort to achieve their goals or lower their internal standards (Taylor et al., 1984). Following the rationale of control theory, we conjecture that if solvers have already had high-quality solutions, they will invest no greater effort than before to develop another high-quality solution, which in turn may decrease the probability of them submitting a new high-quality solution. Furthermore, solvers' incentives to invest additional effort after receiving high-quality scores on their solutions will be further undermined by other factors related to the contest competition. First, the more high-quality solutions a solver has, the more likely they are to win the contest. However, the marginal returns on high-quality solutions will decrease, which negatively affects the solver's incentives. Second, high-quality solutions usually entail exploring new routes and are built on their poorer-performing predecessors (Toubia, 2006), which requires significant additional effort and includes the risk of no returns for exploring other routes. However, contest awards do not compensate for a possible loss, which will negatively affect solvers' willingness to invest additional effort. Studies in wage design have found that not compensating for possible losses resulting from exploration (similar to a seeker's award structure for solvers in a contest) has detrimental effects on company managers' motivation to innovate (Ederer & Manso, 2013). Third, solvers can join other contests to pursue awards once they have had one or more high-quality solutions in the focal contest, which will further suppress their motivation to continue investing in the focal contest.

Therefore, we formulate two opposing hypotheses regarding the relationship between the current and new number of high-quality solutions produced by the focal solver:

HYPOTHESIS 5-1. The current number of high-quality solutions developed by the focal solver positively affects the probability of the focal solver submitting a new high-quality solution in the contest.

HYPOTHESIS 5-2. The current number of high-quality solutions developed by the focal solver negatively affects the probability of the focal solver submitting a new high-quality solution in the contest.

Similar to high-quality solutions, low-quality solutions are also a source of feedback from the seeker to solvers and contain information about what seekers dislike. Thus, solutions scored as low quality by the seeker provide clues about the seeker's preferences and suggest solvers what to avoid when developing a new solution. Conversely, if focal solvers know that their solutions are scored as low quality, their sense of accomplishment or competence will be injured, and their intrinsic incentives may be undermined (Deci & Cascio, 1972). As a result, the focal solver will be less motivated to invest additional effort in the competition. More low-quality solutions from focal solvers will decrease their likelihood of submitting a new high-quality solution.

Because both lines of reasoning lead to different expectations, we formulate two opposing hypotheses to depict the relationship between the current number of low-quality solutions by a focal solver and the probability that he or she will submit a high-quality solution ($P_t(HQ)$):

HYPOTHESIS 6-1. The current number of low-quality solutions developed by the focal solver positively affects the probability of the focal solver submitting a new high-quality solution in the contest.

HYPOTHESIS 6-2. The current number of low-quality solutions developed by the focal solver negatively affects the probability of the focal solver submitting a new high-quality solution in the contest.

4.2.2.3 Effect of high-quality and low-quality solutions by others

We argue that if other solvers have submitted more high-quality solutions, it will lead to a lower probability of the focal solver winning an award, which may lower the focal solver's motivation. As a result, the focal solver will invest less effort in the contest and be less likely to submit another high-quality solution. Therefore, motivation theory predicts:

HYPOTHESIS 7-1. The current number of high-quality solutions developed by other solvers negatively affects the probability of the focal solver submitting a new high-quality solution in the contest.

However, high-quality and low-quality solutions provide the focal solver with feedback from the seeker, which the solver can apply to develop a new high-quality solution. In the contest we study, the focal solver has access to all submitted solutions, and the distribution of the scores of all solutions evaluated by the seeker in this contest, but only knows the specific quality scores for their own solutions. The focal solver has not access to the score of each solution submitted by other solvers. Nevertheless, the focal solver may be able to guess which are high- or low-quality solutions. The more high- or low-quality solutions others have developed in the contest, the more information about seeker preferences the focal solver can deduce. Taken together, we hypothesize:

HYPOTHESIS 7-2. The current number of high-quality solutions developed by others positively affects the probability of the focal solver submitting a new high-quality solution in the contest.

HYPOTHESIS 8. The current number of low-quality solutions developed by others positively affects the probability of the focal solver submitting a new high-quality solution in the contest.

We summarize all hypotheses in Figure 4-2.

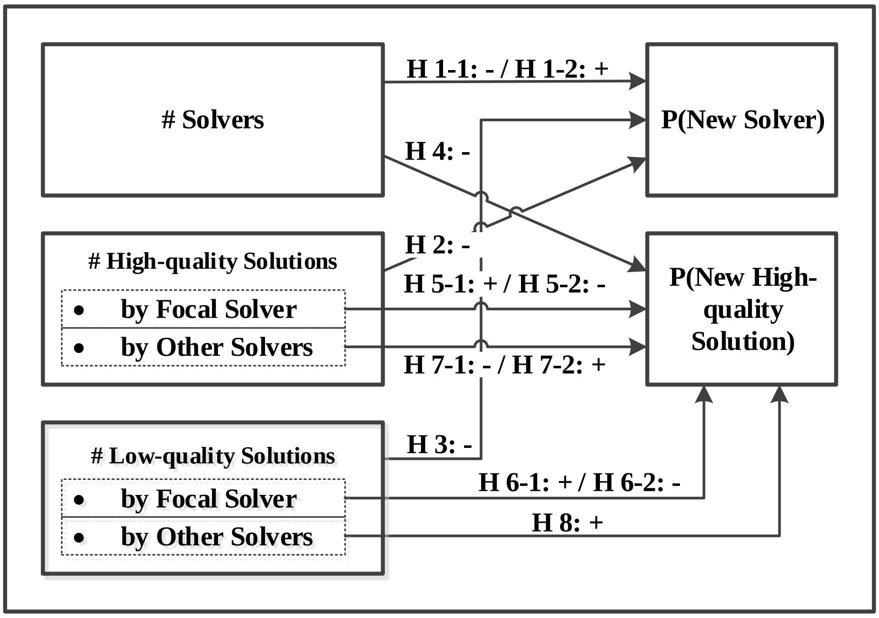

Figure 4–2 Research framework and hypotheses

4.3 Data & Methodology

The hypotheses predict various dynamic relationships between solvers and solutions, and empirically testing them requires specific data. First, solvers need to be allowed to freely join contests and submit multiple solutions during the contest. Second, during the contest, the seeker needs to score solutions, thus enabling us to classify the scored solutions as high-quality solutions that are likely to be awarded and low-quality solutions that are not likely to be awarded. Third, during the contest, solvers must have access to information about the current number of solvers, the current numbers of high-quality and low-quality solutions, and their own number of high-quality and low-quality solutions as scored by the seeker. In the section below, we demonstrate that the data we use satisfy these requirements.

4.3.1 Process within each contest

We collect data from the website of a well-known innovation contest platform. The process of organizing contests on the website is as follows: Seekers describe the problem and the type of solutions they are looking for, determine the number of awards and the monetary amount of each award, and specify the contest duration. During the contest, solvers can freely join and submit solutions. These solutions are visible to all solvers. At the same time, seekers can rate solutions by assigning a score of one to five (with a higher score indicating higher quality). The scoring information (number, or not scored yet) of a particular solution is only visible to the solver who submitted this solution. However, any solver can view a graph with the score distribution of all currently evaluated solutions. During the contest, solution submitting and scoring continues until the contest is over. When the contest is over, the seeker chooses one or more solutions to award according to its evaluation and the award structure. We find that over 50% of the awarded solutions receive a score of five, and nearly 40% receive a score of four. Therefore, we classify solutions scored by the seeker with a four or five as high-quality solutions and solutions scored with a one, two, or three as low-quality solutions. We also have data on when each solver submits a solution and when the seeker scores that solution. The data include 1,789 contests, 20,617 solvers, and 357,057 observations, in which there are 102,114 events of a solver joining the contest and 40,242 (146,204) events of a high-quality (low-quality) solution submission[21].

Table 4–1 Explanatory variables

Explanatory Variables	*Definition*	$P_t(J)$	$P_t(HQ)$
Current number of solvers	The current total number of solvers in a contest. This number is available for any solver who wants to join the contest.	√	√
Current number of high-quality solutions	The current total number of solutions scored with a four or five in a contest. This number is available for any solver who wants to join the contest.	√	
Current number of low-quality solutions	The current total number of solutions scored with a one, two, or three in a contest. This number is available for any solver who wants to join the contest.	√	
Current number of high-quality solutions by the focal solver	The current total number of solutions with a four or five the focal solver has already had in a contest.		√
Current number of high-quality solutions by others	The current total number of solutions with a four or five the other solvers have already had.		√
Current number of low-quality solutions by the focal solver	The current total number of solutions with a one, two, or three the focal solver has already had.		√
Current number of low-quality solutions by others	The current total number of scored solutions with a one, two, or three the other solvers have already had.		√
Control variables	*Definition*	$P_t(J)$	$P_t(HQ)$
Contest duration	The total length in time of the contest (unit: day).	√	√
Elapsed contest duration	(Time elapsed since start of the contest at the moment solution submission) / (Contest duration)	√	√
Number of words in the problem brief	The number of words used to describe the problem brief (unit: 100).	√	√
Average amount of awards	The average award of a contest (unit: $1,000).	√	√
Number of award spots	The number of solutions being awarded after the competition.	√	√
Assured award	Equals 1 if the seeker will award one or more solvers after the contest regardless of the quality of all submitted solutions, and 0 if otherwise.	√	√

[21] Solvers submit solutions, which are subsequently scored by the seeker as high quality, low quality or no score later on. According to the scoring outcomes, a solution submission can be classified as high-quality, low-quality, or no-score solution submission.

4.3.2 Data structure

In line with our research framework (Figure 4-2) and hypotheses, we use the current number of solutions and solvers to explain the probabilities of a solver joining a contest and submitting a new high-quality solution. We also use several contest design characteristics to account for the heterogeneities between different contests (see Table 4–1). We present descriptive statistics of the explanatory variables in Table 4–2.

Table 4–2 Descriptive statistics of explanatory variables

Variables	*M*	*SD*	*Quantiles*				
			Min	*10%*	*50%*	*90%*	*Max*
Current number of high-quality solutions	14.38	27.11	0	0	5	38	350
Current number of low-quality solutions	67.03	93.97	0	0	31	179	717
Current number of solvers	50.69	47.35	0	8	36	114	377
Current number of high-quality solutions by the focal solver	.30	1.54	0	0	0	0	53
Current number of high-quality solutions by others	14.09	26.76	0	0	5	37	350
Current number of low-quality solutions by the focal solver	.68	2.42	0	0	0	2	77
Current number of low-quality solutions by others	66.35	93.36	0	0	31	177	717
Contest duration (unit: day)	10.93	4.44	1	7	10	16	38
Elapsed contest duration	.57	.31	0	.12	.59	.97	1
Number of words in the problem brief (unit: 100)	2.43	1.94	.06	.58	1.93	4.97	14.69
Average amount of awards (unit: 1,000)	.56	.21	.18	.30	.53	.80	2
Number of awards spots	1.38	.88	1	1	1	2	13
Assured award	.38	.48	0	0	0	1	1

Note: The size of the data is 357,057.

4.3.3 Deriving the moments when solvers join contests and submit solutions

The data we apply in the empirical analyses are behavioral data, which mainly contain information about the contest design characteristics, when contests are open and closed, when solutions are submitted and scored, and which scores they received. Our hypotheses link solvers' behaviors (joining contests, submitting high-quality solutions) to the interim information (current number of solvers, current number of high-quality and low-quality solutions) derived from the competition process in the contest. After perceiving these current numbers, solvers still need time to develop a solution. However, the database we use does not contain information about how long it took solvers to develop a solution. Therefore, we exogenously determine when a solver has decided to join a contest and develop a solution. First, we minimize the variability of the time intervals between contests by focusing on one category of contests. The platform contains multiple categories, and we selected the one with the largest number of contests. Second, we assume that all solvers in a contest spend an equal amount of time developing a solution. We conducted a short survey to determine the magnitude of the time intervals. The results show that solvers usually spend one to three hours preparing their first solutions and about half an hour less to develop subsequent solutions. According to this information, we set the time for developing a solution at 2 hours. To investigate the sensitivity of this assumption, we also set this time interval to 1, 1.5, 2.5, and 3 hours; the results are highly similar. The descriptive statistics in Table 4–2 are based on solvers spending 2 hours to develop a solution.

We assume that a solver spent T to develop a solution and that this solver submitted the first solution at t_{first} and a high-quality solution at t_{HQ}. Thus, in the analysis, we assume that this solver decided to join this contest at $t_{first} - T$ and decided to submit the focal high-quality solution at $t_{HQ} - T$. If $t_{first} - T$ and $t_{HQ} - T$ is smaller than 0, this solver decided to join the contest or submit a high-quality solution in a very early phase of the contest. We set a dummy variable equal to 0 if $t_{first} - T$ or $t_{HQ} - T$ is smaller than 0 and to 1 otherwise. In the model specification, we include this dummy as a control variable.

4.3.4 Modeling dependent variables

The dependent variables in our conceptual framework are the probability of a solver joining a contest ($P_t(J)$) and the probability of a solver submitting a high-quality solution ($P_t(HQ)$). We model both probabilities as follows. First, both $P_t(J)$ and $P_t(HQ)$ can be further split into two parts: (1) $P_t(J)$ = P(the solver submits the first solution in the contest) = $P_t(A)P_t(J|A)$, where $P_t(A)$ refers to the probability of a solution being submitted in the contest and $P_t(J|A)$ refers to the probability of the submitted solution being the first solution developed by the focal solver, given the solution being submitted in the contest; and (2) $P_t(HQ)$ = P(the solver submits a high-quality solution in the contest) = $P_t(A)P_t(HQ|A)$, where $P_t(HQ|A)$ is the probability of the submitted solution being of high quality by the focal solver, given the solution being submitted in the contest.

Second, we separately model $P_t(A)$, $P_t(J|A)$, and $P_t(HQ|A)$. Here, $P_t(A)$ is related to the frequency with which solvers submit solutions to the contest, which is measured by the time intervals between sequential solution submission. For a given period, shorter time intervals imply a higher frequency of solution submission. The time intervals of solution submission in the data are not a measure of the time solvers spend developing solutions; rather, they indicate the frequency of solution submission. The frequency of solution submission is a feature at the contest level and can be explained by the contest design characteristics. Thus, we set $P_t(A)$ to be a function of the contest design characteristics. We model the two conditional probabilities, $P_t(J|A)$ and $P_t(HQ|A)$, as functions of the current numbers and contest design characteristics. Furthermore, to account for heterogeneities between different contests and solvers, we include two random effects in the model specification of $P_t(A)$, $P_t(J|A)$, and $P_t(HQ|A)$.

4.3.5 Model specification

We measure $P_t(A)$ with the time intervals between solution submission. After checking the histograms of time intervals and their log-transformation (see Figure 4-3), we find that the log-transformation fits well with the normal distribution (dotted line in the right part of Figure 4-3). Therefore, we specify the following model for the log-transformation of time intervals:

$$\log\left(\mathit{Time\ Intervals}_{ijk}\right) = \beta_0^{Time} + \sum_{m=1}^{M} \beta_m^{Time} x_{mijk} + \omega_i + \varepsilon_j + \sigma_{ijk}\ .$$

Here, subscripts i, j, and k denote that the focal solution is developed by solver i in contest j and that this solution submission is labeled as the kth observation in the whole data set. In addition, M represents the number of independent variables; β_0^{Time} is the intercept, and β_m^{Time} is the coefficient of x_{mijk}; and ω_i, ε_j and σ_{ijk} are three independent random terms, which are set to be normally distributed with mean 0 and variance of

Var(ω),Var(ε), and Var(σ). They represent magnitudes of unexplained heterogeneity between different solvers, contests, and observations, respectively.

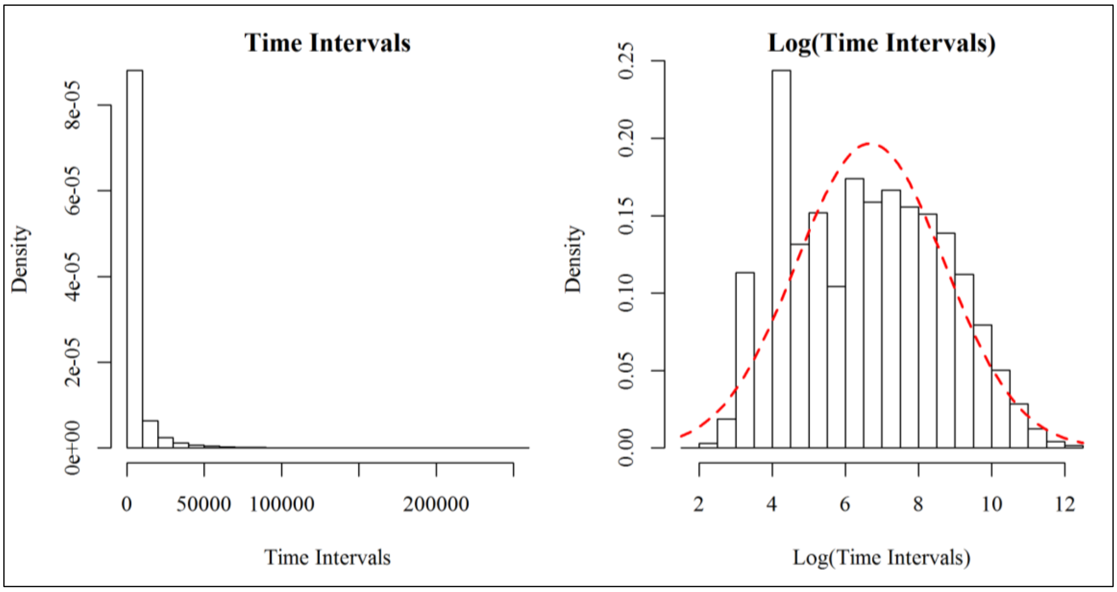

Figure 4–3 Histograms of time intervals of solution submission and its log-transformation

Two conditional probabilities, $P_t(J|A)$, and $P_t(HQ|A)$, can be represented by two binary variables, which we define as follows:

$$\begin{cases} Dummy_{solver} = 1: \text{the solution is the first solution developed by the} \\ \qquad\qquad\qquad \text{focal solver given it is submitted in the contest} \\ Dummy_{solver} = 0: \text{otherwise} \end{cases}$$

$$\begin{cases} Dummy_{solution} = 1: \text{the solution developed by the focal solver is of} \\ \qquad\qquad\qquad \text{high quality given it is submitted in the contest} \\ Dummy_{solution} = 0: \text{otherwise} \end{cases}$$

We can model both conditional probabilities with logistic regressions:

$$\text{logit}\left(P\left(Dummy_{solver} = 1\right)_{ijk}\right) = \beta_0^{Solver} + \sum_{m=1}^{M} \beta_m^{Solver} x_{mijk} + \omega_i + \varepsilon_j \text{, and}$$

$$\text{logit}\left(P\left(Dummy_{solution} = 1\right)_{ijk}\right) = \beta_0^{Solution} + \sum_{m=1}^{M} \beta_m^{Solution} x_{mijk} + \omega_i + \varepsilon_j \text{,}$$

where i, j, k, M, β_0^{Solver}, β_m^{Solver}, $\beta_0^{Solution}$, $\beta_m^{Solution}$, ω_i, and ε_j have the same meaning as their counterparts in the model for time intervals. We estimate the parameters β_0, β_m, Var(ω),Var(ε), and Var(σ) in the linear model and two logistic models using restricted maximum likelihood. To facilitate estimating convergence, we normalize continuous variables x_m in logistic models as x'_m. Using the normalized independent variables, we get the coefficient estimation β'_m. Then, we can obtain the original beta estimation β_m and standard errors with the following transformation: $\beta_m = \beta'_m / sd(x_m)$ and $Std.Error(\beta_m) = Std.Error(\beta'_m) / sd(x_m)$, where $sd(x_m)$ is the standard deviation of x_m. Table 4–3 reports the correlation matrix for the log-transformation of time intervals, two dummy variables, and their corresponding independent variables.

Table 4–3 Correlation matrix for log-transformation of time intervals, two dummy variables and their corresponding independent variables

Variables	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*
Log(time intervals)	6.68	2.03	1.00																
Dummy: solver	.29	.45	.39	1.00															
Dummy: solution	.11	.32	.02	–.08	1.00														
Dummy: lag information	.90	.30	–.05	–.14	.03	1.00													
Current number of solvers	50.69	47.35	–.18	–.08	–.08	.24	1.00												
Current number of high-quality solutions	14.38	27.11	–.09	–.10	.15	.18	.42	1.00											
Current number of low-quality solutions	67.03	93.97	–.13	–.11	.00	.24	.64	.53	1.00										
Current number of high-quality solutions by the focal solver	.30	1.54	–.01	–.12	.22	.07	.00	.25	.09	1.00									
Current number of high-quality solutions by others	14.09	26.76	–.09	–.09	.14	.18	.42	1.00	.54	.20	1.00								
Current number of low-quality solutions by the focal solver	.68	2.42	–.04	–.18	.10	.10	.07	.17	.26	.39	.15	1.00							
Current number of low-quality solutions by others	66.35	93.36	–.13	–.10	.00	.24	.64	.53	1.00	.08	.54	.24	1.00						
Elapsed contest duration	.57	.31	–.10	–.14	–.03	.41	.47	.28	.39	.09	.28	.12	.38	1.00					
Number of words of problem brief	2.28	1.89	.02	–.05	.05	.04	–.09	.01	.03	.05	.00	.06	.02	.04	1.00				
Average amount of awards	.61	.25	–.08	–.02	–.04	–.01	.28	.10	.14	–.02	.10	.02	.14	.00	.09	1.00			
Number of awards spots	1.41	.98	–.02	–.02	.06	.01	.03	.14	.07	.04	.14	.03	.07	.01	.06	–.39	1.00		
Contest duration	11.79	4.56	.06	–.02	.00	.05	.20	.12	.19	.05	.12	.08	.19	–.06	.10	.11	–.04	1.00	
Assured award	.42	.49	.01	–.01	.06	.04	.07	.15	.14	.06	.15	.05	.14	–.06	–.18	–.15	.12	.10	1.00

4.4 Empirical Results

We report our results in three subsections. First, we test the influence of contest design characteristics on $P_t(A)$. Second, we report how $P_t(J|A)$, and $P_t(HQ|A)$ change with their corresponding independent variables. Third, we compare the magnitudes of the significant effects in the models for $P_t(J|A)$, and $P_t(HQ|A)$. In the linear and logistic models, we report two model fit measures: R^2-fixed, which refers to the percentage variance of the independent variable explained by the fixed effects, and R^2-all, which is the percentage variance explained by the fixed and random effects (Johnson, 2014; Nakagawa & Schielzeth, 2013).

Table 4–4 Linear regression of time intervals between solution submissions

Coefficients	*DV: Log(Time Intervals)*
Fixed Effects	
Intercept	7.641*** (129.640)
Elapsed contest duration	–.642*** (–54.289)
Number of words of problem brief (unit: 100)	.41*** (6.419)
Average amount of awards (unit: $1,000)	–.790*** (–12.168)
Number of awards spots	–.103*** (–6.715)
Contest duration (unit: day)	.32*** (11.458)
Assured award (Yes: 1 or No: 0)	–.56* (–2.166)
Random Effects	
Var(ω)	.412
Var(ε)	.229
Var(σ)	3.373
R^2-fixed	.023
R^2-all	.179

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: T-values are in parentheses for fixed effects. The total number of observations is 357,057, and the number of solvers and contests are 20,617 and 1,789.

4.4.1 Frequency of solution submission

We use time intervals to represent the frequency of solution submission. Given a fixed period, shorter time intervals between subsequent solution submissions imply a higher $P_t(A)$. We report the results in Table 4–4.

The results include various significant effects. First, the coefficient for elapsed contest duration is negative and highly significant (–.642, $p < .001$). This reflects that as time goes by, contests receive solutions more frequently. Second, the contest design characteristics affect the frequency of solution submission. Contests with fewer words to describe the problem (.041, $p < .001$), higher average awards (–.790, $p < .001$), more awards (–.103, $p < .001$), and a guarantee to award solutions (–.056, $p < .05$) receive significantly more solutions. Third, the significant and positive effect of contest duration (0.032, $p < .001$) on time intervals indicates that contests with a longer competition period tend to have longer time intervals between solution submissions.

4.4.2 Probabilities of new solvers and high-quality solutions

As we discussed, $P_t(J|A)$, and $P_t(HQ|A)$ could be influenced by the current numbers of solvers and low/high quality solutions, as well as the contest design characteristics. We begin by estimating simple models by relating $P_t(J|A)$, and $P_t(HQ|A)$ to the current numbers of solvers and solutions. Then, we test the full models by including contest design characteristics to control for the heterogeneity between different contests. We present these results in Table 4–5. In this table, Model 1 and Model 2 report results for $P_t(J|A)$, and Model 3 and Model 4 report results for $P_t(HQ|A)$. Models 1 and 3 use the simple model specification, and Models 2 and 4 use the full model specification.

Models 1 and 2 include several significant effects on $P_t(J|A)$. First, the coefficient of the current number of solvers in both models is negative and significant, indicating that $P_t(J|A)$ decreases when the contest has more solvers. Thus, we find empirical support for $H_{1\text{-}1}$ but not for $H_{1\text{-}2}$. Second, the coefficients of the current number of high-quality and low-quality solutions are also negative and significant, so $P_t(J|A)$ also decreases when the contest has more high-quality and low-quality solutions, in support of H_2 and H_3. The coefficient of the dummy variable for missing information is significant and negative, indicating that solvers who have information about the current number of solvers and solutions are less likely to become new solvers. Note that all effects of current numbers of solvers and solutions on $P_t(J|A)$ are robust, regardless of whether the contest design characteristics are included in the model. In addition, we find several significant effects of the contest design characteristics. The results show that contests with fewer words to describe the problem, fewer awards, and a guarantee to award solutions have higher $P_t(J|A)$.

Models 3 and 4 show several significant effects on $P_t(HQ|A)$. First, the coefficients of the current number of solvers and the current number of high-quality solutions by others are negative and significant, indicating that $P_t(HQ|A)$ decreases when the contest has more solvers and more high-quality solutions developed by others. Therefore, H_4 and $H_{7\text{-}1}$ hold, but $H_{7\text{-}2}$ does not. Second, the coefficients of the current number of high-quality solutions by a focal solver and the current number of low-quality solutions by a focal solver and by others are positive and significant, indicating that the focal solver is more likely to submit a new high-quality solution in a contest if he or she has already submitted more high- or low-quality solutions to the same contest or if other solvers have already had more low-quality solutions in the same contest. Thus, we find support for $H_{5\text{-}1}$, $H_{6\text{-}1}$, and H_8 but not for $H_{5\text{-}2}$ and $H_{6\text{-}2}$. Third, the significant, positive effect of the dummy variable for missing information reveals that submitted solutions are more likely to be of high quality if their solvers can see interim information about the current number of solvers and solutions. Again, the effects of the current numbers are robust regardless of whether the model specification includes or excludes contest design characteristics. Last, Model 4 indicates several significant effects of contest design characteristics. It shows that contests with more words to describe the problem, lower average awards, more awards, and a guarantee to award the solution have higher $P_t(HQ|A)$. We summarize the empirical results in Figure 4-4, where "+" and "–" mean positive and negative effects, respectively.

Table 4–5 Results for conditional probabilities of solver joining a contest and developing a high-quality solution

	$P_t(J\|A)$		$P_t(HQ\|A)$	
Coefficients	*Model 1*	*Model 2*	*Model 3*	*Model 4*
Fixed Effects				
Intercept	.150***	.135***	–3.603***	–3.917***
	(7.872)	(6.629)	(–72.129)	(–66.171)
Dummy variable for missing information (0: missing, 1: no missing)	–.893***	–.886***	.237***	.235***
	(–58.635)	(–58.271)	(8.898)	(8.832)
Current n number of high-quality solutions (A)	–.004***	–.004***		
	(–11.863)	(–11.919)		
Current number of low-quality solutions (B)	–.001***	–.001***		
	(–10.274)	(–10.172)		
Current number of solvers	–.005***	–.005***	–.004***	–.004***
	(–23.656)	(–24.143)	(–9.261)	(–9.036)
Current number of high-quality solutions by the focal solver (C)			.102***	.102***
			(26.551)	(26.546)
Current number of high-quality solutions by others			–.007***	–.007***
			(–14.636)	(–14.651)
Current number of low-quality solutions by the focal solver (D)			.068***	.068***
			(25.089)	(25.066)
Current number of low-quality solutions by others (E)			.003***	.003***
			(14.740)	(14.538)
Number of words of problem brief (unit: 100)		–.065***		.098***
		(–12.841)		(4.952)
Average amount of awards (unit: $1,000)		.055		–.577**
		(1.128)		(–2.848)
Number of awards spots		–.029*		.125**
		(–2.524)		(2.655)
Contest duration (unit: day)		.002		–.013
		(.918)		(–1.533)
Assured award (Yes: 1; No: 0)		.050*		.709***
		(2.490)		(9.041)
Random Effects				
Solver level (Var(ω))	.532	.532	1.463	1.467
Contest level (Var(ε))	.118	.104	2.478	2.300
R^2-fixed	.063	.066	.018	.050
R^2-all	.218	.217	.553	.557
Test for "A-B"	–.003***	–.003***		
	(–7.538)	(–7.618)		
Test for "C-D"			.034***	.034***
			(6.157)	(6.164)

Test for "C-E"	.099***	.099***
	(25.820)	(25.820)
Test for "D-E"	.066***	.066***
	(23.887)	(23.874)

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: T values are in parentheses for fixed effects. The total number of observations is 357,057, and the number of solvers and contests are 20,617 and 1,789.

As a robustness check, we set five different values to approximate the time that solvers spend developing a solution, which affects the number of solvers and solutions they saw when starting the development process. The empirical results we have presented are based on the value of two hours, which may influence the results of the models for the conditional probability of the submitted solution being the first solution and the conditional probability of the submitted solution being of high quality ($P_t(J|A)$, and $P_t(HQ|A)$). Therefore, we reestimate models for both conditional probabilities. The results (see Appendix K) show that the signs and significance of all effects are robust and insensitive to different values of the assumed development time.

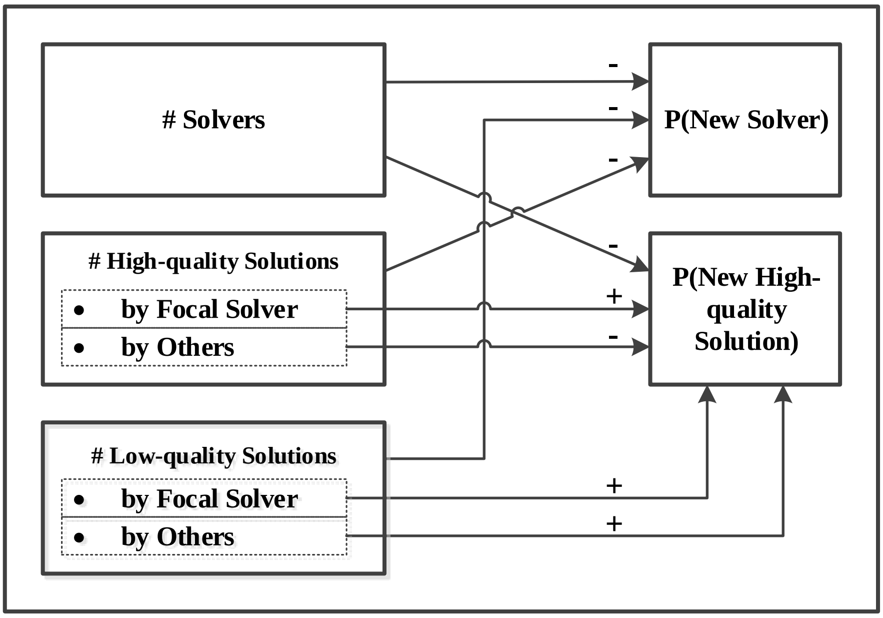

Figure 4–4 The significant effects in the research framework

4.4.3 Magnitudes of the effects

So far, we have tested the significance of the relationships between solvers and high-quality and low-quality solutions depicted in the research framework. Next, we compare the magnitudes of these effects.[22]

Both high-quality and low-quality solutions in a contest negatively affect the probability of new solvers joining the contest (see Table 4–5). The comparison of both effects (see the test for "A-B" in Table 4–5) shows that the coefficient of high-quality solutions is significantly larger in absolute terms than the coefficient of low-quality solutions, which suggests that the current number of high-quality solutions has a stronger negative effect on potential solvers joining a contest than the current number of low-quality solutions. Figure 4-5 shows the marginal effects of both high-quality solutions and low-quality solutions on $P_t(J|A)$, fixing the other independent variables at their median values. As the current number of low-quality solutions increases from 0 to 88, $P_t(J|A)$ decreases from .379 to .356. However, $P_t(J|A)$ decreases from .375 to .298 as the current number of high-quality solutions changes in the same interval[23].

We also compare the magnitudes of the positive effects of high-quality solutions developed by the focal solver and the low-quality solutions developed by the focal solver and other solvers on $P_t(HQ|A)$. The results (see the tests for "C-D," "C-E," and "D-E" in Table 4–5) indicate that high-quality solutions developed by the focal solver have the largest effect on the probability of the focal solver submitting a new high-quality solution. Low-quality solutions developed by the focal solver come in as second, and low-quality solutions developed by other solvers have the smallest effect.

[22] To facilitate the comparison, we draw the marginal effects of independent variables on the same dependent variable in Figures 4-5 and 4-6 using the same range of independent variables. We also draw the marginal effect of each independent variable in separate figures using its 95% quantile range (2.5%–97.5%) (See Appendix L).

[23] The effects of both current numbers on $P_t(J|A)$ in their 95% quantile range (2.5%–97.5%) can be seen in Part B, Appendix L.

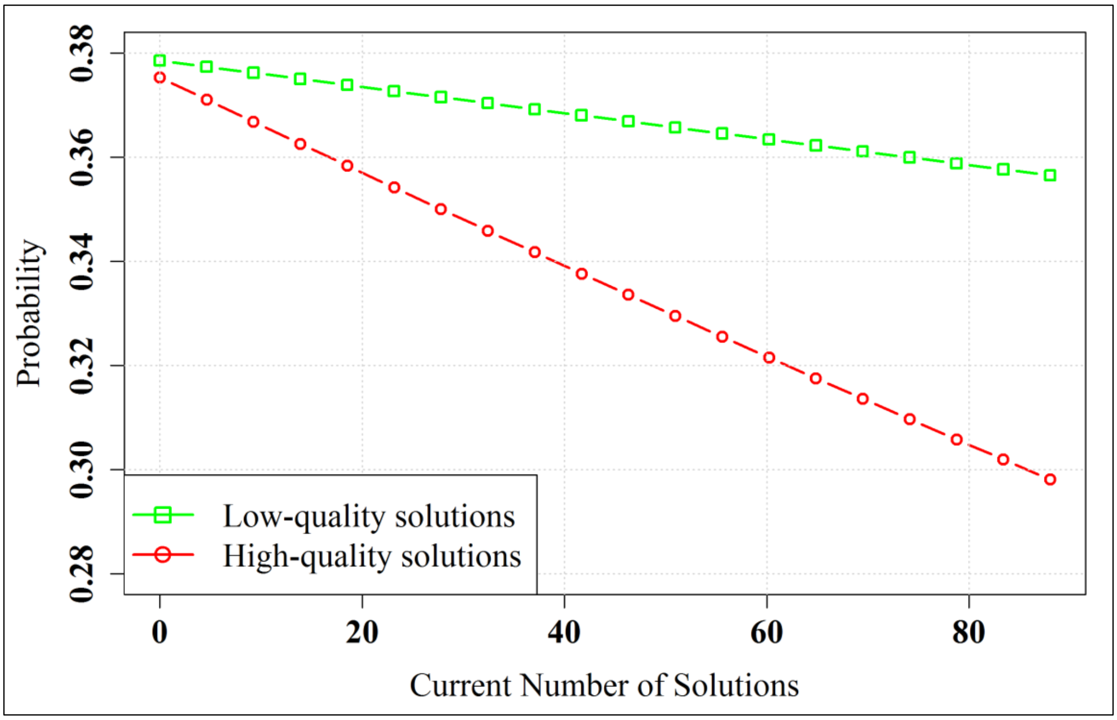

Figure 4–5 The effects of the current number of high-quality and low-quality solutions on the probability of solvers joining a contest[24]

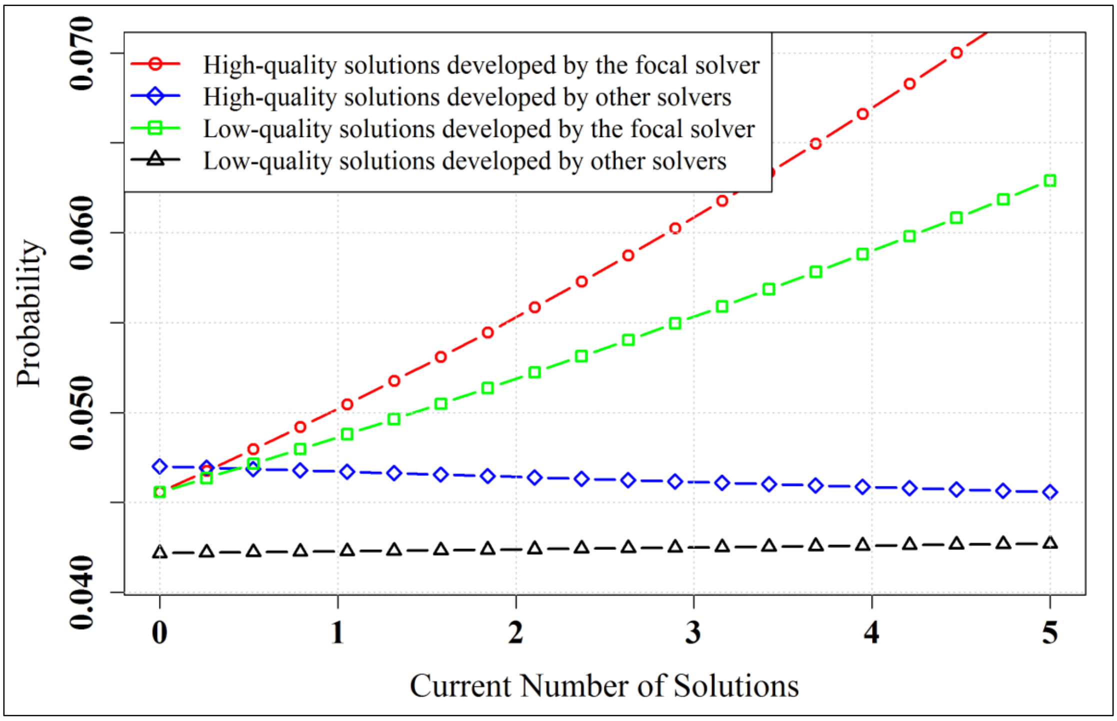

Figure 4–6 The effects of four current numbers of solutions on the probability of solvers submitting a new high-quality solution[25]

[24] The range of current number of solutions (0 - 88) is 95% quantile range (2.5% -97.5%) of the current number of high-quality solutions.

[25] The other independent variables are set at their median values.

We present the marginal effects of three current numbers, as well as the number of high-quality solutions developed by other solvers, on $P_t(HQ|A)$ in Figure 4-6[26]. The results show that as the current number of high-quality solutions developed by the focal solver increases from 0 to 5, $P_t(HQ|A)$ increases from .046 to .074. However, when the current number of low-quality solutions developed by other solvers changes in the same interval, $P_t(HQ|A)$ increases only from .042 to .043. The results also show that as the current number of high-quality solutions developed by other solvers increases from 0 to 5, $P_t(HQ|A)$ decreases from .047 to .045[27].

In H_4 we predicted that as the number of solvers increases, the probability of a solver submitting a new high-quality solution decreases. We illustrate the empirical size of this negative relationship in Figure 4-7. In the end, the number of high-quality solutions developed by all solvers together will equal the number of solvers times the probability of submitting a high-quality solution, which have opposite effects.

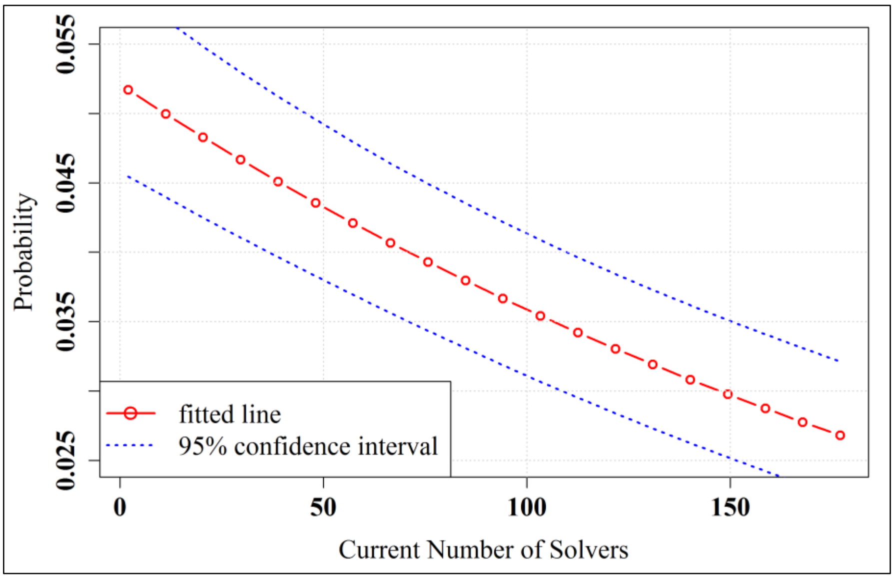

Figure 4–7 The effect of the current number of solvers on the conditional probability of solvers submitting a new high-quality solution[28]

In this section, we demonstrate the predicted relationship between the number of solvers and the number of high-quality solutions. Because a longer contest duration

[26] The effects of four current numbers on $P_t(HQ|A)$ in their 95% quantile range (2.5%–97.5%) can be seen in Part C, Appendix L.

[27] The 95% quantile range (2.5%–97.5%) of both high-quality and low-quality solutions developed by other solvers are much larger than the range shown in Figure 4-6 (from 0 to 5), which can explain why the effects of both current numbers in Figure 4-6 are not obvious.

[28] The range of current number of solvers (2 - 177) is its 95% quantile range (2.5% - 97.5%). The other independent variables are set at their median values.

allows more solvers to join the contest and to submit more high-quality solutions, we divide both numbers by the contest duration (unit: day) to control for the effect of contest duration. Figure 4-8 shows the regression lines and 95% confidence intervals. The positive relationships in the figure provide evidence that the negative effect on the conditional probability of developing a high-quality solution is dominated by the positive effect of the number of solvers, resulting in more high-quality solutions developed by the solver group. Therefore, attracting more solvers garners more high-quality solutions, even though each individual solver will have a lower probability of submitting such a solution

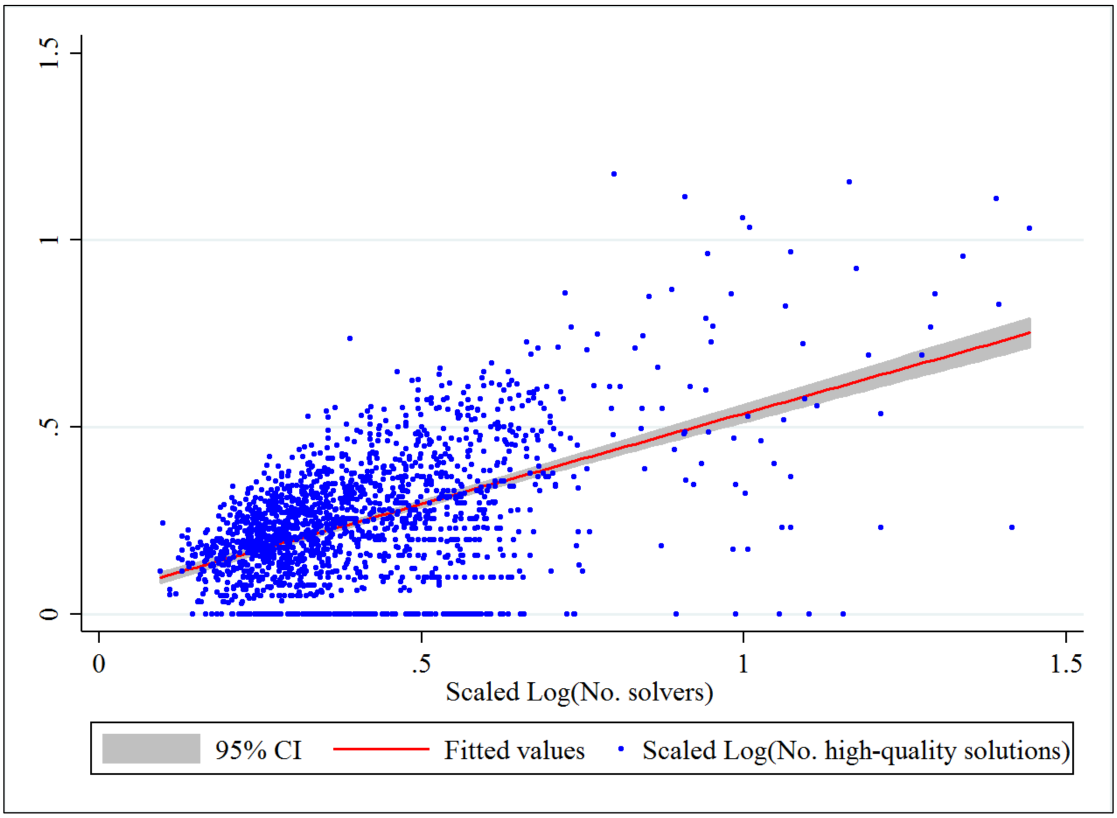

Figure 4–8 The scatter pattern for the scaled number of solvers and high-quality solutions[29]

4.5 Summary & Implications

Firms increasingly use contests to solve innovation problems. Innovation contests simultaneously involve communication between seekers and solvers, and competition among solvers. In a contest, actions such as solvers submitting solutions or the seeker

[29] Both numbers are first log-transformed, and then divided by the contest duration (unit: day).

scoring solutions take place sequentially, so later actions may be affected by previous actions. Based on a large empirical study, we conclude that the decision of a solver to join a contest and the likelihood that he or she will submit a high-quality solution are functions of the current number of solvers and the current number of high-quality solutions. Thus, the number of solvers and high-quality solutions operate as two dynamic processes that interact. Existing literature seldom reveals the dynamics hidden in a contest, opting instead to simplify the contest as a one-stage competition (Boudreau et al., 2011; Terwiesch & Xu, 2008). Some modeling studies have considered dynamics during competition (Aoyagi, 2010; Ederer, 2010), but their assumptions are less realistic. The current study fills this research gap. We build a research framework to explain and reveal the dynamic relationship between the current number of solvers and the current number of high-quality solutions.

Our empirical results include some notable effects. First, a potential solver is less likely to join a contest that already has more solvers, more high-quality solutions, and more low-quality solutions. Second, a solver is more likely to submit a new high-quality solution in a contest in which the focal solver has already submitted more high-quality solutions. Third, a solver is less likely to submit a high-quality solution if the contest already has many solvers or many high-quality solutions developed by others. Fourth, the availability of low-quality solutions, developed by either the focal solver or others, increases the probability of a focal solver submitting a high-quality solution.

4.5.1 Theoretical implications

This study offers several contributions to innovation contest research. First, we demonstrate that in a contest, both the current number of solvers and the current number of high-quality solutions are dynamic processes; that is, the increment of the current number of solvers or high-quality solutions is a function of the current number of solvers and the current number of high-quality solutions. The dynamics in innovation contests suggest that in addition to contest design characteristics, such as awards (Terwiesch & Xu, 2008) and information feedback (Aoyagi, 2010), the number of high-quality solutions in a contest can, in and of itself, have an important effect. Previous research has largely ignored these dynamic effects, our study shows that in order to develop a thorough understanding of innovation contests, researchers need to pay attention to the process of the contest too, and not just treat a contest as a form of one-stage competition.

Second, we revisit the relationship between the number of solvers and contest performance and explore it in a dynamic way. Some studies suggest that more solvers in a contest will lower the entire distribution of outcomes, because each solver in the contest is less motivated by awards (Bothner, Kang, & Stuart, 2007; Fullerton & McAfee, 1999; Garcia & Tor, 2009). However, more solvers in a contest could also mean more paths to the best solutions, such that the number of solvers would be positively correlated with the performance of the best solution (the parallel path effect) (Boudreau et al., 2011; Dahan & Mendelson, 2001). This study goes further by modeling the interdependent changes of both quantities. The results show that though a contest with more solvers may demotivate each solver from submitting a new high-quality solution (H_4), the contest still receives more high-quality solutions, because the increased number of solvers dominates the decreased probability of a solver submitting a high-quality solution. In this sense, the relationship between the number of solvers and the number of high-quality solutions in this study is consistent with the parallel path effect demonstrated in prior work (Boudreau et al., 2011).

Third, the significance of the effects in the research framework (the effect of the number of high-quality solutions developed by other solvers and the number of low-quality solutions developed by the focal solver on $P_t(HQ|A)$) are consistent with the prediction of both motivation theory and the feedback mechanism, suggesting that both forces may underpin the dynamics in this study. Former studies of innovation contests have revealed the negative effects of solvers' deflated motivation (Boudreau et al., 2011; Che & Gale, 2003) and the positive effects of feedback (Jung et al., 2010; Vidal & Nossol, 2011) on contest performance. This study provides empirical confirmation of both effects in the dynamics of an innovation contest. We also find empirical support for both motivation theory and the feedback mechanism, though in different situations. For example, according to the feedback mechanism, high-quality solutions developed by other solvers should be positively correlated with the probability of the focal solver developing a new high-quality solution ($H_{7\text{-}2}$). However, the empirical results are negative, consistent with the prediction of motivation theory ($H_{7\text{-}1}$). According to motivation theory, if a solver has already submitted multiple low-quality solutions, he or she is less likely to develop a new high-quality solution, due to the demotivating effect of getting low scores (negative feedback: $H_{6\text{-}2}$). However, the results show that solvers with more low-quality solutions are more likely to submit a new high-quality solution, consistent with the prediction of the feedback mechanism ($H_{6\text{-}1}$). These findings suggest that motivation theory governs the relationship between solvers and high-quality solutions, but the feedback mechanism holds for the effect of low-quality solutions.

4.5.2 Managerial implications

Our results have several implications for seekers who are organizing innovation contests. Seekers should realize that the processes of solvers joining a contest and solvers submitting high-quality solutions are affected by each other. Solvers show both behaviors, contingent on the current number of solvers, the current number of high-quality solutions, and the current number of low-quality solutions in a contest. Because of these dynamic processes, any deliberate management of solvers and high-quality solutions should be expected to lead to nonlinear responses. In addition, seekers should be judicious in scoring solutions as high quality early in the process of an innovation contest. Although high-quality solutions will encourage submitters to submit another high-quality solution, they simultaneously discourage other solvers. Compared with high-quality solutions, scoring low-quality solutions is a good strategy for a seeker to boost contest performance because this feedback conveys useful information to solvers and helps them develop additional high-quality solutions but does not trigger alarm in other solvers. Finally, a seeker can receive many high-quality solutions by attracting many solvers to the contest. However, a contest with more solvers will deplete more resources of the seeker in interacting with them, and the marginal benefit of additional solvers may decrease as the number of solvers increases. Another strategy for receiving many high-quality solutions is to identify a few skilled solvers from the pool who have joined the contest and score their solutions as high quality. Because the current number of high-quality solutions has the largest positive effect on the probability of the focal solver submitting another high-quality solution, and simultaneously lowers the likelihood of other solvers submitting high-quality solutions, this strategy does not cost much efforts of the seeker to interact with solvers. However, it assumes the seeker's ability to distinguish skilled solvers from the rest. Seekers can choose either strategy, contingent on their own preferences and capabilities

4.5.3 Limitations and opportunities for further research

We acknowledge a few limitations of our study. First, the data do not contain time information about when solvers decide to develop a solution. We use the moment of solution submission to approximate the moment of solvers' forming intentions to join and develop solutions. Although we set the time interval between both events at a range between one and three hours (and find that the results are not sensitive to this range), studies could check the effects based on such time information. Second, high-quality solutions require not only the efforts of solvers but also input from seekers. Seekers can be either highly involved in a contest by actively scoring solutions and/or giving timely feedback to solvers, or they can approach the contest more passively by scoring only a few solutions and/or providing little feedback information to solvers during the competition. The participation level of seekers may have a considerable effect on how solvers develop their solutions. Furthermore, the interim contest outcomes can influence the participation level of seekers. Seekers may become less active if they have already received multiple high-quality solutions. However, this study does not consider the relationship between contest performance and the participation level of the seeker. Not including the seeker's participation level simplifies the conceptual framework and model specification, but it also leaves a gap for further research. Additional studies could focus on the participation level of seekers and analyze its relationship with contest performance. Finally, this study does not consider the heterogeneity of solvers. Previous research has found that ideas proposed by highly motivated solvers are more likely to be implemented (Schemmann, Herrmann, Chappin, & Heimeriks, 2016), and solvers who are more emotionally and cognitively engaged in the innovation contest are more creative (Martinez, 2015). Consistent with such findings, we can conjecture that solvers who are highly motivated or engaged in the innovation contest may be more likely to join the contest and submit high-quality solutions. Further research might explore such moderating effects.

To conclude, this study shows that the performance of innovation contests is not only determined by the contest design (e.g., awards, duration), it is also influenced by the competition among solvers during the contest. We have unfolded the latter effect by introducing two dynamic processes: the increment of the number of solvers and the number of high-quality solutions is a function of the cumulative number of solvers and the cumulative number of high-quality solutions. The empirical results show that both processes exist. This study explores and tests a way to model the competition among solvers, and paves the way to better managing the contests.

5 General Discussion

The main goal of this dissertation is improving the performance of innovation contests. In order to achieve this goal, we have investigated several ways through which innovation contest performance can be influenced. Specifically, we have identified three research gaps:

Research gap 1: the effect of brief on the contest performance is mostly neglected.

Research gap 2: little is known about the effect of diversity on contest performance and how to cope with it in practice.

Research gap 3: no empirical study has extensively investigated the effect of interim information on the contest performance in multiple-round contests.

Accordingly, three research questions are addressed:

RQ1: *What is the effect of the contest brief on contest performance?*

RQ2: *What is the effect of the diversity of solvers on contest performance?*

RQ3: *What is the effect of interim information generated during the competition on contest performance?*

The answers to these questions, which form three empirical chapters, contribute to our understanding of the effectiveness of innovation contests, and help organizers to improve contest performance. This final chapter reiterates the key findings from the three empirical studies, summarizes the theoretical and managerial implications, and ends with a discussion of directions for future research.

5.1 Main Findings

5.1.1 The effects of the contest brief

Chapter 2 examines the effects of the contest brief on the contest performance. Previous research has examined the effects of many contest design elements and solver characteristics on contest performance (Aoyagi, 2010; Bockstedt et al., 2015; Boudreau et al., 2011; Terwiesch & Xu, 2008; Yücesan, 2013), except for one essential aspect of each innovation contest, namely the contest brief. In Chapter 2, based on motivation theory and insights from webpage complexity research, we propose that the readability and the length of the brief can both directly and indirectly influence contest performance in terms of the number of high-quality solutions. Their indirect effects are determined by their effects on the number of high-skilled and low-skilled solvers a contest attracts. The results from the path analyses show that: 1) Both brief readability and brief length directly influence contest performance; 2) Both brief characteristics indirectly influence contest performance through their effects on the numbers of high-skilled and low-skilled solvers; 3) The combined effects of both brief characteristics suggest that a contest with a long and easy-to-read brief will attract more high-quality solutions; 4) The combined effects of both brief characteristics increase as the brief becomes more readable and longer; 5) Both high-skilled and low-skilled solvers can submit high-quality solutions, though this likelihood is significantly greater for high-skilled solvers.

A simulation study in chapter 2 reveals the actual size of the effect of brief. Contest brief can influence the number of high-skilled solvers, the number of low-skilled solvers, and the number of high-quality solutions. The results of the simulation study are shown in the following table. In Table 5–1, the effect of the brief is conceptualized as elasticity and marginal effect. We aggregate the results of the simulation study in Chapter 2 into four conditions: a less readable brief, a more readable brief, a short brief, and a long brief[30]. The results show several patterns: First, as briefs become more readable, the effects of readability become stronger. For example, when the Flesch-Reading Ease score is 40, indicating a less readable brief, 4 increase in readability score will lead to a 0.53 decrease in number of high-skilled solvers. While when the Flesch-Reading Ease score is 80, indicating a more readable brief, the same change in readability score will lead to a 1.04 decrease in the number of high-skilled solvers. Second, as briefs become longer, the brief length elasticity of the three numbers tend to be stronger. While the marginal effect of brief length on the three numbers is complex: as briefs become longer, the marginal effects on the number of high-skilled solvers, low-skilled solvers, and high-quality solutions remains trivial, becomes weaker and stronger, respectively.

30 When deriving the effect of one characteristic of brief, those unchanged variables are set to their median values.

Table 5–1 The effects of contest brief on the number of high- and low-skilled solvers, and the number of high-quality solutions based on the simulation

Characteristics of brief		Elasticity (1% change in one characteristic of brief leads to X% change in three numbers)			Marginal effect (4 increase in readability, or 252 increase in number of words leads to X change in three numbers[31])		
		Number of high-skilled solvers	Number of low-skilled solvers	Number of high-quality solutions	Number of high-skilled solvers	Number of low-skilled solvers	Number of high-quality solutions
Flesch Reading Ease score	40 (less readable brief)	-0.39	0.15	0.28			
	40 → 44				-0.53	2.09	1.61
	80 (more readable brief)	-0.76	0.29	0.58			
	80 → 84				-1.04	2.41	2.24
Number of words in brief	1,000 (short brief)	-0.02	-0.21	0.57			
	1,000 → 1,252				-0.01	-1.16	2.07
	3,000 (long brief)	-0.06	-0.63	1.74			
	3,000 → 3,252				-0.01	-0.76	6.56

The findings make several key contributions to the growing literature on innovation contests. First, it reveals how the contest briefs can influence the contest performance. Its direct and indirect effects on contest performance provide the base on which future studies can continue to explore the effect of contest briefs. Second, this study suggests that besides the extrinsic motivation, solvers can be intrinsically motivated to join a contest, especially when high-skilled solvers are confronted with a contest with a hard-to-read brief. A hard-to-read brief may denote that the project is difficult, but it can attract high-skilled solvers since they think they have the ability to solve it, and they enjoy the feeling of accomplishment. Third, both high-skilled and low-skilled solvers can develop high-quality solutions, which echoes the parallel path effect revealed in former literature (Boudreau et al., 2011; Terwiesch & Xu, 2008). This effect predicts that as the number of solvers increases and more solvers search solutions for an innovation project, the likelihood of finding high-quality solutions increases. Fourth, the total effects of contest briefs reveal that contests with readable and longer briefs tend to have better contest performance. It suggests that solvers who receive clear and

[31] When conducting a simulation study, we set the increment of the score of readability measure and the number of word at 4 and 252 respectively.

detailed information are more likely to develop high-quality solutions. This finding is consistent with the rationale of the dual pathway to creativity model (Baas et al., 2013). Last, this study suggests that how a contest is presented online can influence contest performance. Thus, insights from webpage complexity and/or web communication research (Deng & Poole, 2010; Geissler et al., 2001; Nadkarni & Gupta, 2007) can help to increase our understanding of the process and the effectiveness of innovation contests.

5.1.2 The effects of the diversity of solvers

Chapter 3 investigates the second research question, namely the effects of the diversity of the solver group on contest performance. The effects of work group diversity in the traditional organizations are intensively examined. However, innovation contests feature some characteristics, which distinguish them from the traditional organizations. Thus, insights derived from the studies based on traditional organizations may not be directly applicable in the situation of innovation contests. The effect of the diversity of solvers on contest performance should be examined. In this study, we investigate the effects of diversity in expertise, country of residence, and experience on contest performance, and test the moderating effect of the uncertainty level of the brief on these effects. The results show that 1), there are inverted U-shape relationships between three diversity measures and contest performance; 2), contests with more certain briefs tend to have better performance; 3) the uncertainty level of briefs moderates the curvilinear relationships between diversity and contest performance in such a way that as briefs become more uncertain, the inflection point shifts horizontally from a smaller to a larger value of the diversity measures.

Take the country of residence diversity for example, we predict the number of high-quality solutions based on the empirical results. It shows that compared with receiving less than 10 high-quality solutions when the diversity level is extremely low or high, the seeker can expect to receive about 18 high-quality solutions when the diversity level reaches its optimal level (see Figure 5-1). As the uncertainty of briefs decreases from its extremely high value to its extremely low value, the number of high-quality solutions increases with approximately 9 (see Figure 5-2). When the brief changes from low to high uncertainty (from 0.32 to -0.32[32], which correspond to the mean plus/minus two standard deviations), the inflection point shifts horizontally from a small to a large value of diversity measures (from -0.19 to 0.41 for country of residence diversity, see Figure 5-3). The shifting spans for country of residence diversity account for 19% of its ranges, which suggests a substantial moderating effect of the uncertainty.

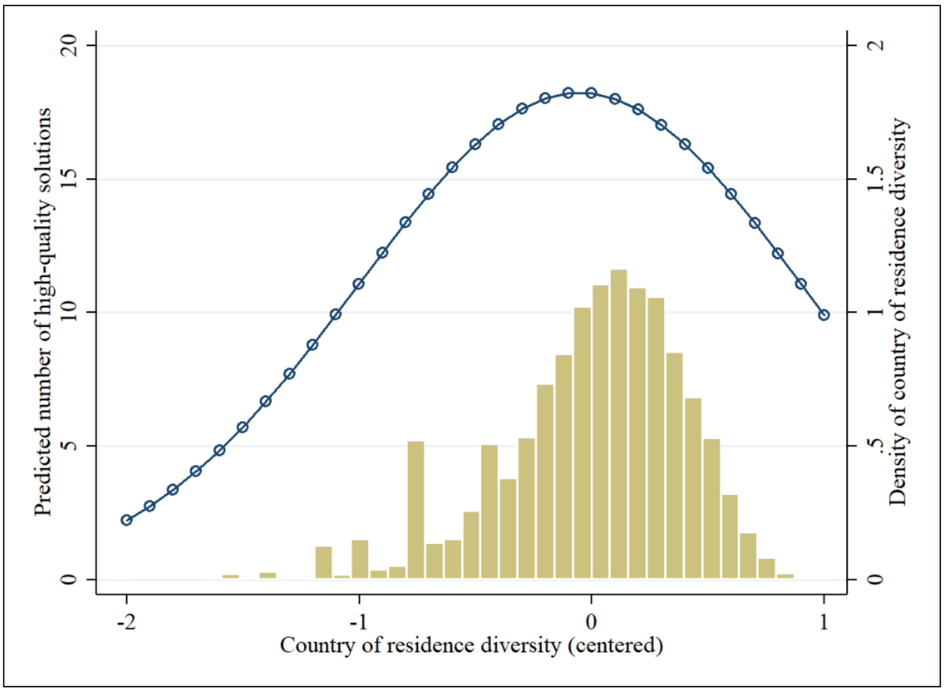

Figure 5–1 The curvilinear effect of country of residence diversity on the contest performance

[32] Large value of uncertainty measure of brief indicates a low uncertainty level. The variable of uncertainty measure is centered.

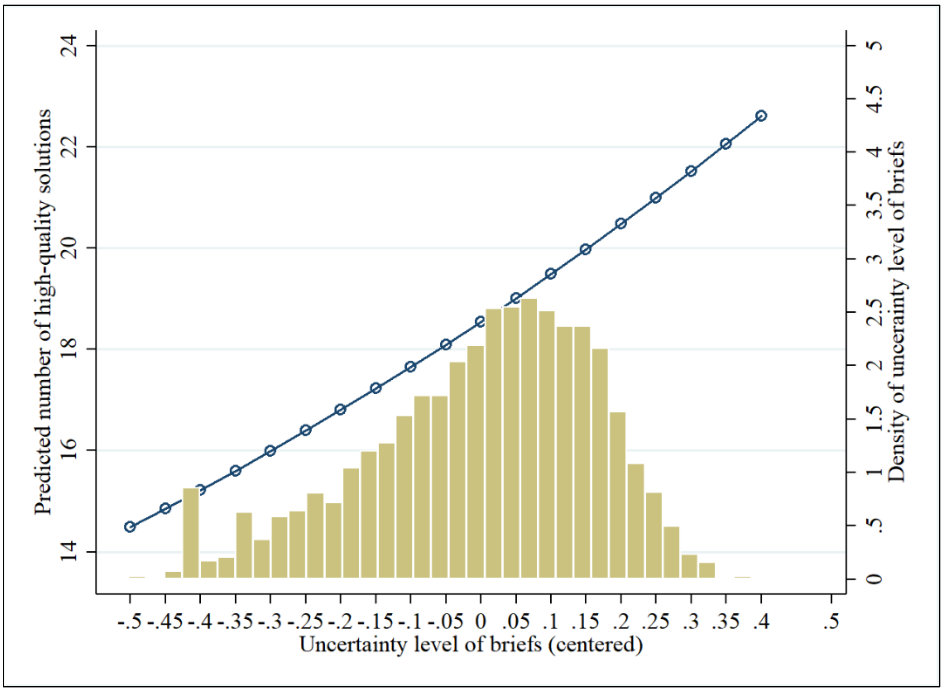

Figure 5–2 The effect of the uncertainty of briefs on the contest performance

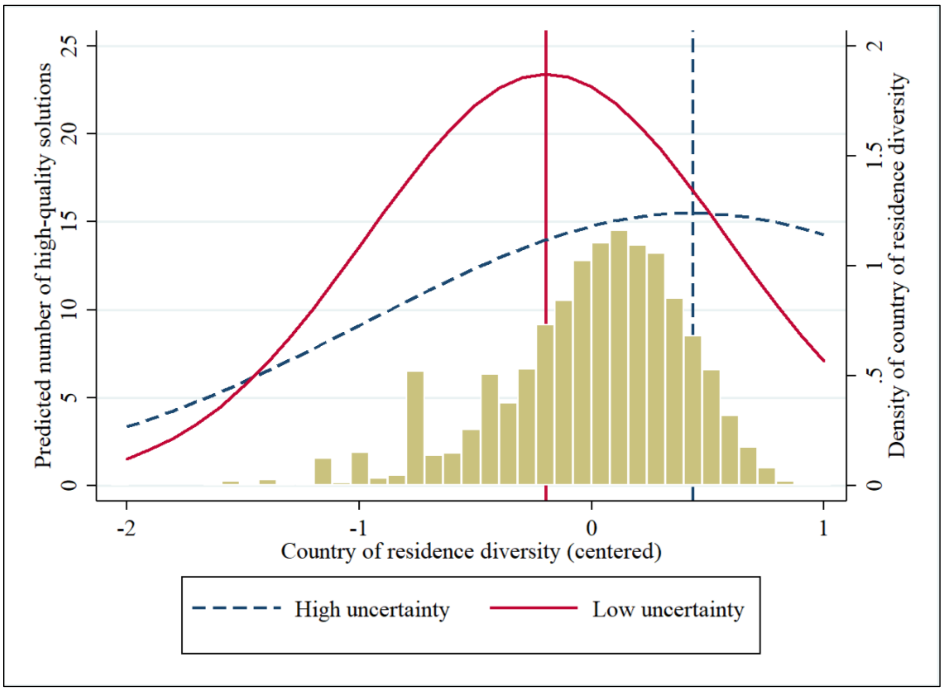

Figure 5–3 The moderating effect of the uncertainty level of a brief on the relationship between the country of residence diversity and the contest performance

This study has several theoretical contributions. First, it reveals that the diversity of solvers does impact contest performance, which extends the applications of diversity theories from traditional organizations to innovation contests. Second, the same non-linear effects of expertise, country of residence, and experience diversity on contest performance suggest that the typology of diversity does not contribute to unfolding the effect of diversity. Unfolding the effect of diversity in innovation contests still requires the understanding of exploiting task-relevant information that underlies the positive effect of diversity on group performance (van Knippenberg et al., 2004). Third, the effects of diversity and the uncertainty level of briefs on contest performance suggest that contests with a less uncertain brief, and a moderate level of solvers diversity will receive more high-quality solutions. This finding echoes the dual pathway creativity model (Baas et al., 2013). According to this model, individuals can develop innovative ideas by investing systematic effort or applying broad and inclusive cognitive categories. Less uncertain briefs can provide solvers the clear information that can facilitates them to develop high-quality solutions by investing systematic effort. The moderate diversity provides solvers the space in which they can explore other perspectives. The combination of both methods, as the results show, generates the most high-quality solutions. Fourth, this study finds a moderating effect of the uncertainty level of briefs, which amplifies the insights about the effects of diversity on group performance. It reveals that the uncertainty introduced by contest briefs results in intentions of solvers seeking information, which in turn, affects solvers processing diverse information attached to solutions developed by other solvers. Last, the moderating effect of contest briefs suggests the relevance of contest briefs when discussing the effectiveness of innovation contests, especially the effect of diversity on contest performance. Hence, this research contributes also to the understanding of the effect of contest briefs.

5.1.3 The effects of interim information about the contest performance

Chapter 4 examines the effects of interim information on contest performance (research question 3). During the competition in an innovation contest, if solvers are allowed to submit multiple solutions, and the seeker can score them, this scoring information can be considered as interim information about the contest performance. This information will affect solvers joining the contest, and investing effort to develop solutions thereafter. Former studies either treat innovation contests as one-round competition, and overlook such effects, or model such effects with less realistic assumptions (e.g. only two agents compete in two-round contests). In this study, we first conceptualize such interim information as the currently available number of solvers, low-quality solutions, and high-quality solutions in a contest. Low- (or high-) quality solutions are scored solutions that are less (or more) likely to be awarded by the seeker when the contest is over. Then, we propose that the interim information can affect solvers joining the contest and submitting high-quality solutions. Based on the predictions of motivation theory and the feedback mechanism, the likelihood of solvers joining a contest and submitting high-quality solutions are set to be functions of the currently available amount of solvers, low-quality solutions, and high-quality solutions in the contest.

Results from the generalized linear mixed models show the following patterns. First, a solver is less likely to join a contest that has already more solvers, more high-quality solutions, and more low-quality solutions. Second, a solver is more likely to submit another high-quality solution if this solver has already submitted more high-quality solutions to the same contest. Third, a solver is less likely to submit a high-quality solution if the contest has already many solvers or many high-quality solutions developed by others. Finally, the availability of low-quality solutions, developed by either the focal solver or others, increases the probability that the focal solver submits a high-quality solution.

This study makes several contributions to innovation contest research. First, it shows that the interim information does affect contest performance. In a contest, both the current number of solvers and the current number of high-quality solutions are dynamic processes: the increment is the function of its stock. It suggests that besides contest design elements (e.g. awards), contest performance can be affected by information about interim contest performance. Second, the relationship between the number of solvers and contest performance is re-examined. Former studies reveal either a negative (Bothner et al., 2007; Fullerton & McAfee, 1999; Garcia & Tor, 2009) or a positive relationship (Boudreau et al., 2011; Dahan & Mendelson, 2001). Results in this study show that although more solvers will make each solver invest less effort to develop high-quality solutions, the increase in the number of solvers dominates the decrease of the probability of a solver submitting a high-quality solution. Thus, more solvers will generate more high-quality solutions. Finally, the significant effects shown in this study are consistent with the predictions of motivation theory and the feedback mechanism, which suggests that both may underpin the dynamics revealed in this study.

5.2 Managerial Implications

Three main chapters in this dissertation focus on how seekers formulate the briefs, manage the diversity of solvers, and cope with the dynamics during the competition. Accordingly, several managerial implications for seekers and managers of the online platforms can be derived.

When seekers plan to formulate a brief, they should realize that the readability and the length of the brief can influence the number of high-skilled and low-skilled solvers, and finally affect contest performance. If seekers want more high-skilled solvers, they could develop less readable briefs. If they would like to attract more low-skilled solvers, the brief should be shorter and more readable. If they want more high-quality solutions, a longer and more readable brief would be a good choice.

Once a contest has started, seekers need to realize that how they score candidate solutions during the competition will affect the probability of new solvers joining the contest, and solvers submitting high-quality solutions. Because of such dynamics, any seeker's subjective efforts of increasing the number of solvers and/or the number of high-quality solutions may result in nonlinear responses. Second, managers should be prudent to score high-quality solutions during the competition. Although high-quality solutions can encourage the solvers who have submitted them to submit additional high-quality solutions, they simultaneously demotivate other solvers. Compared with high-quality solutions, scoring low-quality solutions is a safer strategy since they can help solvers who submit them to submit new high-quality solutions, and do not depress other solvers. Finally, our findings suggest two effective strategies of improving contest performance. The seeker can receive more high-quality solutions by attracting more solvers. This strategy will cost more resources of the seeker to interact with solvers, but may benefit more from the diversity of solvers. The other strategy is relying on high-skilled solvers by scoring their solutions as high-quality, or formulating less readable briefs. This strategy requires less resources of the seeker, but the ability to distinguish the skilled solvers from the rest.

Besides the skill level of solvers, during the competition, seekers need to realize that the diversity of solvers can influence contest performance. the inverted U-shape relationship between diversity and contest performance implies that there is an optimal diversity level for a contest with a given brief. In order to help the seeker to receive more high-quality solutions, the platform is recommended to calculate diversity indices, and to show them to the seeker. The platform can also revise the policy of solvers freely joining the contests, and design some management tools to help the seeker to keep the diversity of solver group at a medium level. Second, the main effects of the uncertainty level of the brief suggests that a certain brief is a better choice than an uncertain one for contest performance. Seekers should use proper adjectives and/or adverbs to convey more certain message to their solvers. Finally, the moderating effect of uncertainty suggests that if the seeker expects to be confronted with a very diverse solver group, an uncertain brief will be a better choice.

5.3 Future Research

The literature review in Chapter 1 suggests that contest design elements, solver characteristics, and the ways in which the seeker manages a contests can influence the contest performance (see Figure 5-4). This dissertation discusses the effects of the contest brief and solvers diversity on contest performance in Chapter 2 and 3, and explores a way of conceptualizing the interim information about contest performance and investigate its effects on contest performance in Chapter 4. Based on the literature review and three empirical studies in this dissertation, several important avenues for the future research are derived.

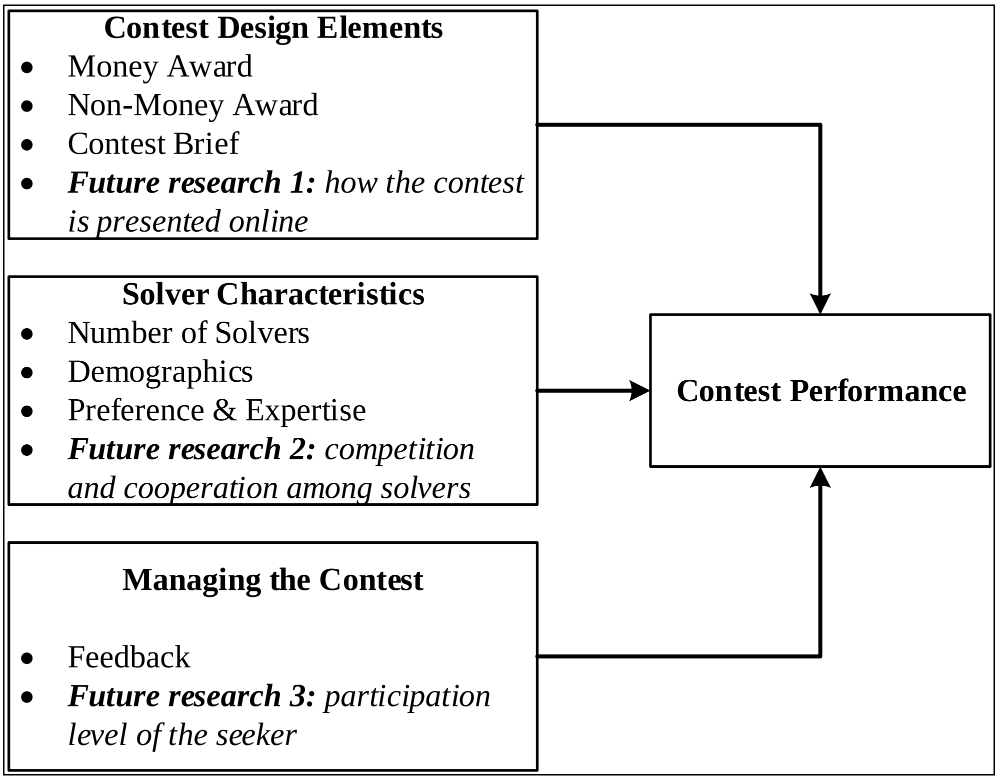

Figure 5–4 Factors that influence the contest performance

First, innovation contests are usually organized online. Therefore, how they are presented online potentially influences how many solvers join a contest, and finally, contest performance. In this dissertation we find some evidence for this. In Chapter 2, we find that brief readability and length influence the number of high-skilled and low-skilled solvers, and ultimately contest performance, which partly echoes previous research (Yang, Chen, & Pavlou, 2009). In Chapter 3, we find that the uncertainty level of contest briefs can influence contest performance directly, and also moderates the effect of solver group diversity on contest performance. The length, readability, and uncertainty level of a brief, as we proposed and tested in this dissertation, influence contest performance. Based on these findings, we can safely conjecture that how the contest design elements are presented online influences contest performance. Previous studies revealed that webpage complexity can impact behaviors of webpage browsers (Geissler et al., 2001; Nadkarni & Gupta, 2007). Based on the findings in this dissertation and in previous studies, more research is needed to understand whether and how presenting characteristic(s) (e.g., size, color, shape, location, font size) of contest design elements can influence contest performance.

Second, this dissertation shows that solvers can be motivated to competitively submit high-quality solutions to design projects. However, besides the competition among solvers, cooperation among them also positively correlates with creativity and innovation. Previous studies show that interacting with diverse individuals and exchanging information and ideas generally have positive effect on innovation (Amabile, Conti, Coon, Lazenby, & Herron, 1996; Perry-Smith & Shalley, 2003). Network ties help individuals gain diverse perspectives (Perry-Smith, 2006), and thus, facilitate them develop various alternatives (Granovetter, 1983). Chapter 3 also reveals that diversity among solvers positively affects contest performance when the diversity level is not too high. Studies on innovation contests begin to explore the role of cooperation. For example, Bullinger, Neyer, Rass, and Moeslein (2010) found a U-shape relationship between the cooperative orientation of solvers and contest performance. However, most studies pay little attention to cooperation, and do not empirically determine the effect of cooperation. Cooperation can be seen as a kind of characteristic of individuals (Obstfeld, 2005). Individuals with cooperation orientation tend to link disconnected individuals together, and facilitate their cooperation (Bullinger et al., 2010). Füller, Hutter, Hautz, and Matzler (2014) classified solvers in innovation-contest communities into six categories according to their position in the social network. Individuals in one main category (“socializers”) could be solvers with high cooperation potential. Therefore, future research is needed to empirically investigate the role of cooperation. Classifying solvers and finding solvers with cooperation orientation can be the first step of such studies.

Third, in innovation contests, innovative solutions require not only the efforts of solvers, but also the inputs from the seeker. Besides monetary awards directly provided by the seeker, seekers can influence contest performance by adopting different participation strategies: Seekers can either be highly involved in the contest by actively scoring solutions and giving timely feedback to solvers, or passively treat the contest by scoring only few solutions and give little feedback information to solvers during the competition. Following former studies in feedback (Jung et al., 2010; Kluger & DeNisi, 1996; Vidal & Nossol, 2011), the participation level of the seeker may have considerable effect on how solvers develop solutions. On the other hand, contest performance can influence the participation level of the seeker: seekers may be less active if they have already received valuable innovation solutions during the contest. Therefore, it is likely that, during the competition, the participation level of the seeker and contest performance affect one another. Three empirical studies in this dissertation, however, do not consider the mutual relationship between the participation level of the seeker and contest performance. Some modeling studies investigated the effect of feedback on contest performance in a multiple-round setting (Aoyagi, 2010; Ederer, 2010). However, they did not consider the mutual relationship between the participation level of the seeker and the contest performance. Thus, future empirical studies are needed to determine the effect of participation level. Insights derived from such studies help the seekers to formulate optimal strategies of how to involve in the contests for better contest performance.

5.4 Conclusion

To conclude, innovation contests are effective and efficient for firms to receive high-quality solutions to their projects. Previous studies have offered many insights about how to improve contest performance. Inspired by these studies, this dissertation explores several new factors through which managers can leverage contest performance. It reveals that the contest brief, the diversity of the solver group, and the interim information about the contest performance influence contest performance. We hope these findings enrich the scientific knowledge about online innovation contests, enlighten future research, and help managers to achieve better contest performance.

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7 Appendices

7.1 Appendix A: Comparisons of Model Specification

In the comparison, we use the threshold of 0.15 to determine the skill level of solvers. Comparison results based on other thresholds (0.11, 0.13, 0.17, or 0.19) are the same as them based on the threshold of 0.15.

Table 7–1 Comparison results for the number of high-skilled solvers

PRM		BIC=22863.006	AIC=22812.793	Prefer	Over	Evidence
vs	NBRM	BIC=19018.434	dif=3844.573	NBRM	PRM	Very strong
		AIC=18961.944	dif=3850.849	NBRM	PRM	
		LRX2=3852.849	prob=0.000	NBRM	PRM	p=0.000
vs	ZIP	BIC=22161.924	dif=701.083	ZIP	PRM	Very strong
		AIC=22099.157	dif=713.636	ZIP	PRM	
		Vuong=8.809	prob=0.000	ZIP	PRM	p=0.000
vs	ZINB	BIC=19034.987	dif=3828.019	ZINB	PRM	Very strong
		AIC=18965.944	dif=3846.849	ZINB	PRM	
NBRM		BIC=19018.434	AIC=18961.944	Prefer	Over	Evidence
vs	ZIP	BIC=22161.924	dif=-3143.490	NBRM	ZIP	Very strong
		AIC=22099.157	dif=-3137.213	NBRM	ZIP	
vs	ZINB	BIC=19034.987	dif=-16.553	NBRM	ZINB	Very strong
		AIC=18965.944	dif=-4.000	NBRM	ZINB	
		Vuong=-0.005	prob=0.498	NBRM	ZINB	p=0.498
ZIP		BIC=22161.924	AIC=22099.157	Prefer	Over	Evidence
vs	ZINB	BIC=19034.987	dif=3126.936	ZINB	ZIP	Very strong
		AIC=18965.944	dif=3133.213	ZINB	ZIP	
		LRX2=3135.213	prob=0.000	ZINB	ZIP	p=0.000

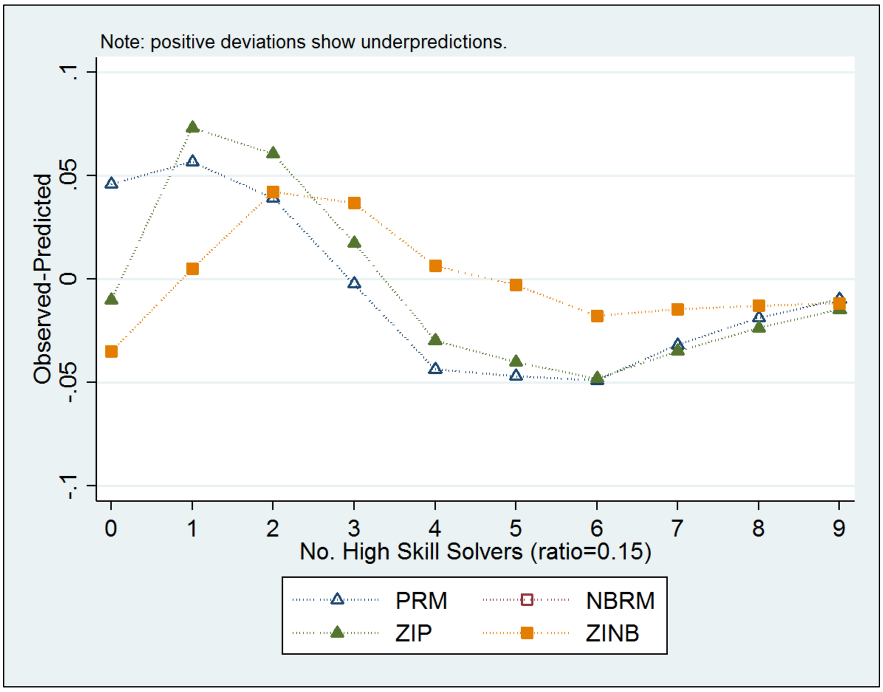


Figure 7–1 Comparison of residual fit for the number of high-skilled solvers

Note: the smaller residual, the better fit.

Table 7–2 Comparison results for the number of low-skilled solvers

PRM		BIC=92746.936	AIC=92696.722	Prefer	Over	Evidence
vs	NBRM	BIC=33719.119	dif=59027.816	NBRM	PRM	Very strong
		AIC=33662.629	dif=59034.093	NBRM	PRM	
		LRX2=59036.093	prob=0.000	NBRM	PRM	p=0.000
vs	ZIP	BIC=92717.666	dif=29.270	ZIP	PRM	Very strong
		AIC=92654.899	dif=41.823	ZIP	PRM	
		Vuong=1.049	prob=0.147	ZIP	PRM	p=0.147
vs	ZINB	BIC=33735.673	dif=59011.263	ZINB	PRM	Very strong
		AIC=33666.629	dif=59030.093	ZINB	PRM	
NBRM		BIC=33719.119	AIC=33662.629	Prefer	Over	Evidence
vs	ZIP	BIC=92717.666	dif=-58998.546	NBRM	ZIP	Very strong
		AIC=92654.899	dif=-58992.270	NBRM	ZIP	
vs	ZINB	BIC=33735.673	dif=-16.553	NBRM	ZINB	Very strong
		AIC=33666.629	dif=-4.000	NBRM	ZINB	
		Vuong=5.375	prob=0.000	ZINB	NBRM	p=0.000
ZIP		BIC=92717.666	AIC=92654.899	Prefer	Over	Evidence
vs	ZINB	BIC=33735.673	dif=58981.993	ZINB	ZIP	Very strong
		AIC=33666.629	dif=58988.270	ZINB	ZIP	
		LRX2=58990.270	prob=0.000	ZINB	ZIP	p=0.000

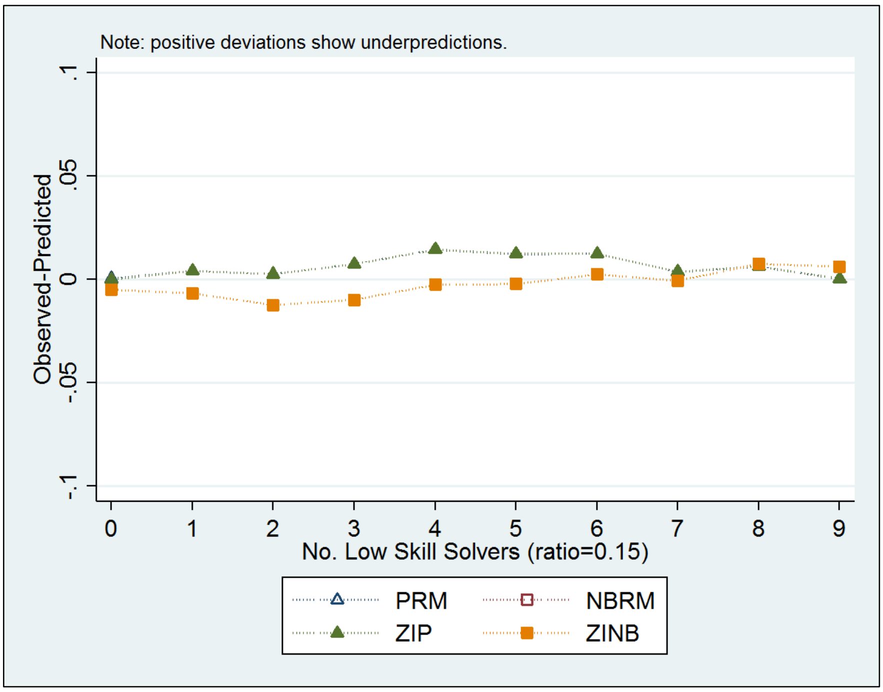


Figure 7–2 Comparison of residual fit for the number of low-skilled solvers

Table 7–3 Comparison results for the number of high-quality solutions

PRM		BIC=91224.038	AIC=91161.272	Prefer	Over	Evidence
vs	NBRM	BIC=29564.882	dif=61659.157	NBRM	PRM	Very strong
		AIC=29495.838	dif=61665.433	NBRM	PRM	
		LRX2=61667.433	prob=0.000	NBRM	PRM	p=0.000
vs	ZIP	BIC=79469.614	dif=11754.424	ZIP	PRM	Very strong
		AIC=79394.295	dif=11766.977	ZIP	PRM	
		Vuong=10.983	prob=0.000	ZIP	PRM	p=0.000
vs	ZINB	BIC=29526.472	dif=61697.567	ZINB	PRM	Very strong
		AIC=29444.875	dif=61716.396	ZINB	PRM	
NBRM		BIC=29564.882	AIC=29495.838	Prefer	Over	Evidence
vs	ZIP	BIC=79469.614	dif=-49904.733	NBRM	ZIP	Very strong
		AIC=79394.295	dif=-49898.456	NBRM	ZIP	
vs	ZINB	BIC=29526.472	dif=38.410	ZINB	NBRM	Very strong
		AIC=29444.875	dif=50.963	ZINB	NBRM	
		Vuong=3.600	prob=0.000	ZINB	NBRM	p=0.000
ZIP		BIC=79469.614	AIC=79394.295	Prefer	Over	Evidence
vs	ZINB	BIC=29526.472	dif=49943.143	ZINB	ZIP	Very strong
		AIC=29444.875	dif=49949.419	ZINB	ZIP	
		LRX2=49951.419	prob0.000	ZINB	ZIP	p=0.000

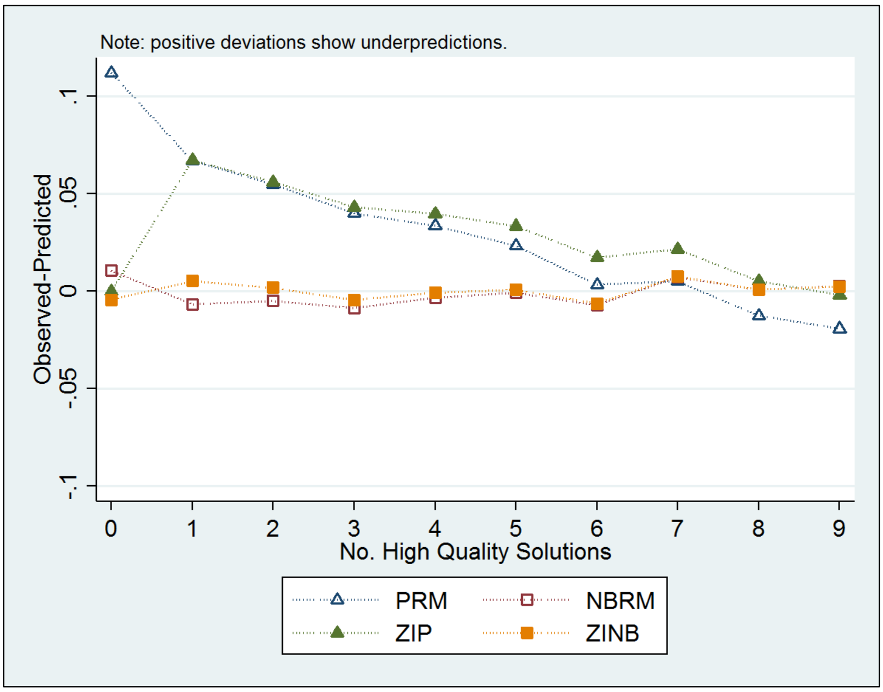


Figure 7–3 Comparison of residual fit for the number of high-quality solutions

7.2 Appendix B: Detailed Results of Path Analysis

Table 7–4 Detailed results of path analysis

	Readability Measure: Flesch-Kincaid Reading Ease (unit: 10)					Readability Measure: Flesch-Kincaid Grade Level				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19
DV: High-Skilled Solvers										
Readability Measure	-0.036**	-0.061***	-0.076***	-0.091***	-0.094***	0.009	0.017*	0.022**	0.028***	0.028**
	(-2.882)	(-4.438)	(-5.109)	(-5.564)	(-5.369)	(1.430)	(2.572)	(3.068)	(3.579)	(3.385)
No. Words for Briefs (unit: 100)	-0.001	0.000	0.000	-0.001	-0.002	-0.002	-0.001	-0.002	-0.003	-0.004
	(-0.323)	(-0.012)	(-0.114)	(-0.254)	(-0.446)	(-0.587)	(-0.409)	(-0.569)	(-0.744)	(-0.909)
No. awards (centered by 1)	0.114***	0.101***	0.088***	0.111***	0.096***	0.113***	0.099***	0.085***	0.107***	0.092***
	(8.143)	(6.631)	(5.129)	(5.872)	(4.930)	(8.072)	(6.513)	(4.989)	(5.716)	(4.752)
Average Awards (unit: $, normalized)	0.190***	0.198***	0.200***	0.211***	0.214***	0.192***	0.200***	0.202***	0.213***	0.216***
	(14.618)	(14.090)	(13.430)	(12.665)	(11.809)	(14.665)	(14.152)	(13.499)	(12.743)	(11.889)
Award Assured (0: no, 1: yes)	-0.240***	-0.336***	-0.450***	-0.600***	-0.705***	-0.243***	-0.340***	-0.455***	-0.605***	-0.712***
	(-10.001)	(-12.802)	(-15.999)	(-18.519)	(-20.197)	(-10.068)	(-12.870)	(-16.055)	(-18.540)	(-20.273)
Contest duration (unit: day, normal-	0.005	0.003	-0.003	-0.019	-0.019	0.004	0.002	-0.004	-0.020	-0.021
ized)	(0.447)	(0.223)	(-0.181)	(-1.147)	(-1.117)	(0.368)	(0.130)	(-0.272)	(-1.257)	(-1.22)
Category: graphic (0: web, 1: graphic)	0.648***	0.629***	0.674***	0.922***	1.048***	0.643***	0.621***	0.665***	0.911***	1.038***
	(25.021)	(22.346)	(22.577)	(26.565)	(28.188)	(24.893)	(22.114)	(22.290)	(26.282)	(27.928)
Constant	1.514***	1.556***	1.543***	1.320***	1.156***	1.212***	1.029***	0.881***	0.514***	0.328***
	(17.790)	(16.783)	(15.449)	(12.000)	(9.817)	(22.288)	(17.277)	(13.666)	(7.166)	(4.309)
Over-dispersion										
Constant	-0.483***	-0.401***	-0.334***	-0.230***	-0.178***	-0.481***	-0.399***	-0.331***	-0.226***	-0.175***
	(-26.961)	(-26.931)	(-27.812)	(-28.870)	(-28.810)	(-27.079)	(-27.131)	(-28.073)	(-29.165)	(-29.114)
DV: Low-Skilled Solvers										
Readability Measure	0.034**	0.037**	0.038**	0.037**	0.036**	-0.011*	-0.012*	-0.013*	-0.012*	-0.012*

	(3.028)	(3.308)	(3.434)	(3.440)	(3.387)	(-2.076)	(-2.268)	(-2.365)	(-2.378)	(-2.333)
No. Words for Briefs (unit: 100)	-0.022***	-0.022***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.020***	-0.020***
	(-5.675)	(-5.759)	(-5.751)	(-5.681)	(-5.645)	(-5.503)	(-5.568)	(-5.552)	(-5.480)	(-5.445)
No. awards (centered by 1)	0.122***	0.124***	0.125***	0.121***	0.122***	0.122***	0.124***	0.126***	0.122***	0.123***
	(6.604)	(6.789)	(6.916)	(6.771)	(6.864)	(6.621)	(6.806)	(6.933)	(6.788)	(6.880)
Average Awards (unit: $, normalized)	0.232***	0.229***	0.229***	0.228***	0.227***	0.231***	0.228***	0.227***	0.227***	0.226***
	(15.773)	(15.721)	(15.785)	(15.872)	(15.931)	(15.752)	(15.699)	(15.764)	(15.852)	(15.913)
Award Assured (0: no, 1: yes)	0.299***	0.295***	0.300***	0.299***	0.297***	0.300***	0.295***	0.301***	0.299***	0.297***
	(11.932)	(11.924)	(12.246)	(12.322)	(12.285)	(11.855)	(11.845)	(12.161)	(12.236)	(12.198)
Contest duration (unit: day, normalized)	0.120***	0.117***	0.115***	0.115***	0.114***	0.120***	0.117***	0.116***	0.115***	0.114***
	(9.990)	(9.923)	(9.883)	(9.934)	(9.887)	(9.996)	(9.930)	(9.891)	(9.940)	(9.893)
Category: graphic (0: web, 1: graphic)	1.578***	1.551***	1.526***	1.470***	1.448***	1.584***	1.556***	1.531***	1.475***	1.453***
	(64.658)	(64.296)	(63.719)	(62.588)	(61.907)	(65.122)	(64.772)	(64.190)	(63.065)	(62.383)
Constant	2.107***	2.135***	2.159***	2.226***	2.259***	2.416***	2.467***	2.501***	2.564***	2.589***
	(27.277)	(28.048)	(28.683)	(30.064)	(30.711)	(47.448)	(49.072)	(50.245)	(52.312)	(53.107)
Over-dispersion										
Constant	-0.367***	-0.383***	-0.391***	-0.400***	-0.405***	-0.367***	-0.382***	-0.390***	-0.400***	-0.405***
	(-43.039)	(-43.363)	(-43.454)	(-43.226)	(-43.213)	(-43.053)	(-43.387)	(-43.480)	(-43.252)	(-43.236)
DV: High-Quality Solution										
No. High-Skilled Solvers (ratio in column)	0.018**	0.021***	0.021***	0.020**	0.023***	0.018**	0.021***	0.022***	0.021**	0.023***
	(3.133)	(3.563)	(3.624)	(3.365)	(3.680)	(3.127)	(3.570)	(3.641)	(3.394)	(3.704)
No. Low-Skilled Solvers (ratio in column)	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(5.323)	(5.250)	(5.455)	(5.791)	(5.725)	(5.342)	(5.275)	(5.484)	(5.819)	(5.758)
Readability Measure	0.065**	0.067**	0.068**	0.067**	0.068**	-0.050***	-0.051***	-0.051***	-0.051***	-0.052***
	(3.017)	(3.107)	(3.134)	(3.115)	(3.153)	(-4.582)	(-4.63)	(-4.652)	(-4.647)	(-4.664)
No. Words for Briefs (unit: 100)	0.059***	0.059***	0.059***	0.059***	0.059***	0.061***	0.061***	0.061***	0.061***	0.061***
	(10.032)	(10.049)	(10.086)	(10.097)	(10.083)	(10.353)	(10.379)	(10.417)	(10.425)	(10.415)
No. awards (centered by 1)	0.129***	0.130***	0.132***	0.132***	0.133***	0.129***	0.130***	0.131***	0.131***	0.132***
	(5.760)	(5.809)	(5.882)	(5.891)	(5.912)	(5.730)	(5.779)	(5.851)	(5.859)	(5.881)

Average Awards (unit: $, normalized)	0.079**	0.078**	0.078**	0.080**	0.079**	0.083**	0.082**	0.083**	0.084**	0.084**
	(3.077)	(3.047)	(3.060)	(3.120)	(3.116)	(3.251)	(3.219)	(3.229)	(3.291)	(3.287)
Award Assured (0: no, 1: yes)	0.568***	0.579***	0.584***	0.582***	0.589***	0.557***	0.568***	0.573***	0.572***	0.578***
	(14.013)	(14.096)	(14.090)	(13.973)	(14.083)	(13.621)	(13.718)	(13.719)	(13.612)	(13.727)
Contest duration (unit: day, normalized)	0.042*	0.043*	0.043*	0.043*	0.044*	0.041	0.043*	0.043*	0.042*	0.043*
	(1.992)	(2.057)	(2.068)	(2.049)	(2.099)	(1.945)	(2.011)	(2.023)	(2.007)	(2.055)
Category: graphic (0: web, 1: graphic)	0.383***	0.386***	0.384***	0.373***	0.368***	0.385***	0.388***	0.387***	0.376***	0.371***
	(7.835)	(7.921)	(7.877)	(7.634)	(7.520)	(7.910)	(8.002)	(7.959)	(7.711)	(7.599)
Constant	1.339***	1.318***	1.317***	1.336***	1.332***	2.142***	2.143***	2.148***	2.163***	2.167***
	(8.948)	(8.756)	(8.762)	(8.985)	(8.986)	(22.435)	(22.389)	(22.455)	(22.622)	(22.596)
Zero-inflated										
Award Assured (0: no, 1: yes)	-15.378***	-16.674***	-14.025***	-12.331***	-16.331***	-15.454***	-14.276***	-13.309***	-12.316***	-16.410***
	(-29.919)	(-33.328)	(-28.430)	(-24.721)	(-33.130)	(-29.468)	(-28.060)	(-26.566)	(-24.283)	(-32.724)
Constant	-2.729***	-2.735***	-2.736***	-2.731***	-2.732***	-2.744***	-2.750***	-2.751***	-2.747***	-2.748***
	(-17.993)	(-17.930)	(-17.914)	(-17.970)	(-17.966)	(-17.865)	(-17.797)	(-17.781)	(-17.836)	(-17.833)
Over-dispersion										
Constant	0.048***	0.048***	0.048***	0.048***	0.048***	0.047***	0.047***	0.047***	0.047***	0.046***
	(33.163)	(33.185)	(33.189)	(33.212)	(33.221)	(33.103)	(33.128)	(33.131)	(33.152)	(33.162)
Test										
No. High-Skilled Solvers - No. Low-Skilled Solvers	0.014*	0.017**	0.018**	0.017**	0.019**	0.014*	0.018**	0.018**	0.017**	0.019**
	(2.361)	(2.820)	(2.882)	(2.638)	(2.970)	(2.353)	(2.824)	(2.894)	(2.663)	(2.990)

t statistics in parentheses, size of the sample: 3,931

* p < 0.05, ** p < 0.01, *** p < 0.001

7.3 Appendix C: Definition of Elasticity and Marginal Effect

(taking the variable of number of word for example)

1. The number of words is increased by a small part $\Delta Words$, $Words_1 \rightarrow Words_2$, $\Delta Words = Words_2 - Words_1$.

2. Because of the increasing of number of words, the number of high-skilled and low-skilled solvers is changing:
$High\text{-}Skilled_1 = f_{\mathrm{HS}}(FK, Words_1, Control) \rightarrow High\text{-}Skilled_2 = f_{\mathrm{HS}}(FK, Words_2, Control)$, $\Delta High\text{-}Skilled = High\text{-}Skilled_2 - High\text{-}Skilled_1$, and
$Low\text{-}Skilled_1 = f_{\mathrm{LS}}(FK, Words_1, Control) \rightarrow Low\text{-}Skilled_2 = f_{\mathrm{LS}}(FK, Words_2, Control)$, $\Delta Low\text{-}Skilled = Low\text{-}Skilled_2 - Low\text{-}Skilled_1$

3. Because of the changing of number of words, high-skilled, and low-skilled solvers, the number of high-quality solutions is changing:
$High\ Quality\ Solutions_1 = f_{HQS}(High\text{-}Skilled_1, Low\text{-}Skilled_1, FK, Words_1, Control) \rightarrow High\ Quality\ Solutions_2 = f_{HQS}(High\text{-}Skilled_2, Low\text{-}Skilled_2, FK, Words_2, Control)$, $\Delta High\ Quality\ Solutions = High\ Quality\ Solutions_2 - High\ Quality\ Solutions_1$

We define

- the word elasticity of high-skilled solvers as $E_{Word\text{-}High\ Skilled} = (\Delta High\text{-}Skilled / High\text{-}Skilled_1) / (\Delta Words / Words_1)$,
- the word elasticity of low-skilled solvers as $E_{Word\text{-}Low\ Skilled} = (\Delta Low\text{-}Skilled / Low\text{-}Skilled_1) / (\Delta Words / Words_1)$, and
- the word elasticity of high quality solutions as $E_{Word\text{-}Solutions} = (\Delta High\ Quality\ Solutions / High\ Quality\ Solutions_1)/(\Delta Words / Words_1)$.
- the marginal effect of word on high-skilled solvers as $M_{Word\text{-}High\ Skilled} = \Delta High\text{-}Skilled / \Delta Words$,
- the marginal effect of word on low-skilled solvers as $M_{Word\text{-}Low\ Skilled} = \Delta Low\text{-}Skilled / \Delta Words$, and
- the marginal effect of word on high-quality solutions as $M_{Word\text{-}Solutions} = \Delta High\ Quality\ Solutions / \Delta Words$.

We measure the readability of briefs using the Flesch Reading Ease score. Both the readability measure and the number of words are set to be 20 singal values with the same interval from their minmum value to maxmum value. Unchanged variables are set to their median values: readability measure (unit: 10): 6.74, number of words (unit: 100): 5.09, number of award spots: 1, average awards (unit: $): 657, awards are assured to pay, contest duration (unit: day): 12, category is graphic, marginal increase of readability measure: 4, and marginal increase of brief words: 252. Solvers are defined as high-skilled solvers if their (Number of awarded soultions/Number of submitted soultions) ≥ 0.19, and low-skilled solvers if otherwise.

7.4 Appendix D: Robustness Check for Path Analysis

Table 7–5 Effect of readability and brief words on high-skilled solvers

Readability Measure:	Flesch-Kincaid Reading Ease (unit: 10)					Flesch-Kincaid Grade Level				
	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19
Readability Measure	-0.036**	-0.061***	-0.076***	-0.091***	-0.094***	0.009	0.017*	0.022**	0.028***	0.028***
	(-2.882)	(-4.438)	(-5.108)	(-5.564)	(-5.368)	(1.430)	(2.572)	(3.068)	(3.579)	(3.384)
No. Words for Briefs	-0.001	-0.000	-0.000	-0.001	-0.002	-0.002	-0.001	-0.002	-0.003	-0.004
(unit: 100)	(-0.323)	(-0.012)	(-0.114)	(-0.254)	(-0.446)	(-0.587)	(-0.409)	(-0.569)	(-0.744)	(-0.909)
No. awards (centered by 1)	0.114***	0.101***	0.088***	0.111***	0.096***	0.113***	0.099***	0.085***	0.107***	0.092***
	(8.142)	(6.630)	(5.129)	(5.871)	(4.929)	(8.071)	(6.512)	(4.988)	(5.716)	(4.751)
Average Awards (unit: $,	0.190***	0.198***	0.200***	0.211***	0.214***	0.192***	0.200***	0.202***	0.213***	0.216***
normalized)	(14.616)	(14.088)	(13.429)	(12.664)	(11.807)	(14.663)	(14.151)	(13.498)	(12.742)	(11.888)
Award Assured (0: no, 1:	-0.240***	-0.336***	-0.450***	-0.600***	-0.705***	-0.243***	-0.340***	-0.455***	-0.605***	-0.712***
yes)	(-10.000)	(-12.800)	(-15.997)	(-18.516)	(-20.194)	(-10.067)	(-12.869)	(-16.053)	(-18.538)	(-20.270)
Contest duration (unit:	0.005	0.003	-0.003	-0.019	-0.019	0.004	0.002	-0.004	-0.020	-0.021
day, normalized)	(0.447)	(0.223)	(-0.181)	(-1.147)	(-1.117)	(0.368)	(0.130)	(-0.272)	(-1.257)	(-1.220)
Category: graphic (0: web,	0.648***	0.629***	0.674***	0.922***	1.048***	0.643***	0.621***	0.665***	0.911***	1.038***
1: graphic)	(25.018)	(22.343)	(22.574)	(26.562)	(28.185)	(24.890)	(22.111)	(22.287)	(26.279)	(27.924)
Constant	1.514***	1.556***	1.543***	1.320***	1.156***	1.212***	1.029***	0.881***	0.514***	0.328***
	(17.788)	(16.781)	(15.447)	(11.999)	(9.816)	(22.285)	(17.275)	(13.664)	(7.165)	(4.309)
Over-dispersion										
Constant	-1.113***	-0.925***	-0.770***	-0.529***	-0.411***	-1.110***	-0.918***	-0.762***	-0.520***	-0.402***
	(-30.001)	(-24.896)	(-21.412)	(-15.274)	(-11.826)	(-30.049)	(-24.911)	(-21.388)	(-15.172)	(-11.689)
Observations	3931	3931	3931	3931	3931	3931	3931	3931	3931	3931
Pseudo R^2	0.033	0.032	0.036	0.049	0.057	0.033	0.032	0.035	0.048	0.056

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7–6 Effect of readability and brief words on low-skilled solvers

Readability Measure:	Flesch-Kincaid Reading Ease (unit: 10)					Flesch-Kincaid Grade Level				
	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19
Readability Measure	0.034**	0.037***	0.038***	0.037***	0.036***	-0.011*	-0.012*	-0.013*	-0.012*	-0.012*
	(3.028)	(3.308)	(3.434)	(3.439)	(3.386)	(-2.076)	(-2.268)	(-2.364)	(-2.378)	(-2.332)
No. Words for Briefs	-0.022***	-0.022***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.020***	-0.020***
(unit: 100)	(-5.675)	(-5.758)	(-5.751)	(-5.680)	(-5.644)	(-5.502)	(-5.567)	(-5.551)	(-5.479)	(-5.445)
No. awards (centered by 1)	0.122***	0.124***	0.125***	0.121***	0.122***	0.122***	0.124***	0.126***	0.122***	0.123***
	(6.603)	(6.788)	(6.915)	(6.770)	(6.863)	(6.620)	(6.805)	(6.932)	(6.787)	(6.879)
Average Awards (unit: $,	0.232***	0.229***	0.229***	0.228***	0.227***	0.231***	0.228***	0.227***	0.227***	0.226***
normalized)	(15.771)	(15.719)	(15.783)	(15.870)	(15.929)	(15.750)	(15.697)	(15.762)	(15.850)	(15.911)
Award Assured (0: no, 1:	0.299***	0.295***	0.300***	0.299***	0.297***	0.300***	0.295***	0.301***	0.299***	0.297***
yes)	(11.931)	(11.923)	(12.244)	(12.320)	(12.283)	(11.854)	(11.843)	(12.160)	(12.234)	(12.197)
Contest duration (unit:	0.120***	0.117***	0.115***	0.115***	0.114***	0.120***	0.117***	0.116***	0.115***	0.114***
day, normalized)	(9.989)	(9.922)	(9.882)	(9.933)	(9.885)	(9.995)	(9.929)	(9.890)	(9.939)	(9.892)
Category: graphic (0: web,	1.578***	1.551***	1.526***	1.470***	1.448***	1.584***	1.556***	1.531***	1.475***	1.453***
1: graphic)	(64.649)	(64.288)	(63.711)	(62.580)	(61.899)	(65.113)	(64.763)	(64.182)	(63.057)	(62.375)
Constant	2.107***	2.135***	2.159***	2.226***	2.259***	2.416***	2.467***	2.501***	2.564***	2.589***
	(27.273)	(28.045)	(28.679)	(30.061)	(30.707)	(47.442)	(49.066)	(50.238)	(52.306)	(53.100)
Over-dispersion										
Constant	-0.844***	-0.881***	-0.901***	-0.922***	-0.932***	-0.843***	-0.880***	-0.899***	-0.920***	-0.931***
	(-36.326)	(-38.217)	(-39.135)	(-39.842)	(-40.275)	(-36.283)	(-38.171)	(-39.087)	(-39.795)	(-40.228)
Observations	3931	3931	3931	3931	3931	3931	3931	3931	3931	3931
Pseudo R^2	0.081	0.081	0.081	0.078	0.077	0.081	0.081	0.080	0.078	0.077

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7–7 Effect of readability and number of words on number of high-quality solutions

Readability Measure:	Flesch-Kincaid Reading Ease (unit: 10)					Flesch-Kincaid Grade Level				
	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19

No. High-Skilled Solvers	0.018**	0.021***	0.021***	0.020***	0.023***	0.018**	0.021***	0.022***	0.021***	0.023***
(ratio in column)	(3.133)	(3.563)	(3.623)	(3.365)	(3.680)	(3.127)	(3.569)	(3.640)	(3.393)	(3.704)
No. Low-Skilled Solvers	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
(ratio in column)	(5.323)	(5.249)	(5.454)	(5.791)	(5.724)	(5.342)	(5.274)	(5.483)	(5.818)	(5.757)
Flesch-Kincaid Reading	0.065**	0.067**	0.068**	0.067**	0.068**	-0.050***	-0.051***	-0.051***	-0.051***	-0.052***
Ease (unit: 10)	(3.017)	(3.107)	(3.133)	(3.114)	(3.153)	(-4.581)	(-4.629)	(-4.651)	(-4.647)	(-4.663)
No. Words for Briefs	0.059***	0.059***	0.059***	0.059***	0.059***	0.061***	0.061***	0.061***	0.061***	0.061***
(unit: 100)	(10.031)	(10.048)	(10.085)	(10.096)	(10.081)	(10.352)	(10.378)	(10.416)	(10.424)	(10.414)
No. awards (centered by 1)	0.129***	0.130***	0.132***	0.132***	0.133***	0.129***	0.130***	0.131***	0.131***	0.132***
	(5.759)	(5.808)	(5.881)	(5.890)	(5.911)	(5.730)	(5.779)	(5.851)	(5.859)	(5.880)
Average Awards (unit: $,	0.079**	0.078**	0.078**	0.080**	0.079**	0.083**	0.082**	0.083**	0.084***	0.084**
normalized)	(3.077)	(3.046)	(3.059)	(3.120)	(3.116)	(3.250)	(3.219)	(3.229)	(3.291)	(3.287)
Award Assured (0: no, 1:	0.568***	0.579***	0.584***	0.582***	0.589***	0.557***	0.568***	0.573***	0.572***	0.578***
yes)	(14.011)	(14.094)	(14.088)	(13.971)	(14.081)	(13.619)	(13.716)	(13.717)	(13.610)	(13.725)
Contest duration (unit:	0.042*	0.043*	0.043*	0.043*	0.044*	0.041	0.043*	0.043*	0.042*	0.043*
day, normalized)	(1.991)	(2.057)	(2.067)	(2.049)	(2.098)	(1.945)	(2.011)	(2.022)	(2.006)	(2.054)
category: graphic (0: web,	0.383***	0.386***	0.384***	0.373***	0.368***	0.385***	0.388***	0.387***	0.376***	0.371***
1: graphic)	(7.834)	(7.920)	(7.876)	(7.633)	(7.520)	(7.909)	(8.001)	(7.958)	(7.710)	(7.598)
Constant	1.339***	1.318***	1.317***	1.336***	1.332***	2.142***	2.143***	2.148***	2.163***	2.167***
	(8.947)	(8.755)	(8.761)	(8.983)	(8.984)	(22.432)	(22.386)	(22.452)	(22.620)	(22.593)
Zero-inflated										
Award Assured (0: no, 1:	-34.921***	-19.744***	-19.747***	-19.744***	-19.751***	-19.748***	-19.765***	-19.769***	-19.764***	-19.774***
yes)	(-67.927)	(-39.458)	(-40.022)	(-39.574)	(-40.062)	(-37.651)	(-38.844)	(-39.456)	(-38.960)	(-39.427)
Constant	-2.729***	-2.734***	-2.736***	-2.731***	-2.732***	-2.744***	-2.750***	-2.751***	-2.747***	-2.748***
	(-17.992)	(-17.928)	(-17.913)	(-17.968)	(-17.964)	(-17.864)	(-17.796)	(-17.780)	(-17.835)	(-17.832)
Over-dispersion										
Constant	0.111***	0.110***	0.110***	0.110***	0.110***	0.108***	0.108***	0.108***	0.108***	0.107***
	(3.669)	(3.660)	(3.663)	(3.663)	(3.640)	(3.581)	(3.572)	(3.575)	(3.575)	(3.551)
Test										

No. High-Skilled Solvers -	0.014^{*}	0.017^{**}	0.018^{**}	0.017^{**}	0.019^{**}	0.014^{**}	0.018^{**}	0.018^{**}	0.017^{**}	0.019^{**}
No. Low-Skilled Solvers	(2.361)	(2.820)	(2.881)	(2.637)	(2.969)	(2.353)	(2.824)	(2.894)	(2.662)	(2.990)
Observations	3931	3931	3931	3931	3931	3931	3931	3931	3931	3931

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.5 Appendix E: Simple ZINB Model for the Number of High-quality Solutions

Table 7–8 Total effect of readability and brief length on the number of high-quality solutions

DV: No. high-quality solutions	3-1	3-2
Flesch-Kincaid reading ease (unit: 10)	0.067**	
	(3.092)	
Flesch-Kincaid grade level		-0.050***
		(-4.500)
No. words for briefs (unit: 100)	0.052***	0.054***
	(8.704)	(8.993)
No. awards (centered by 1)	0.168***	0.168***
	(6.916)	(6.885)
Average awards (unit: $, normalized)	0.150***	0.155***
	(4.492)	(4.617)
Award assured (0: no, 1: yes)	0.578***	0.569***
	(13.936)	(13.622)
Contest duration (unit: day, normalized)	0.061**	0.061**
	(2.834)	(2.808)
Category: graphic (0: web, 1: graphic)	0.634***	0.640***
	(12.887)	(12.948)
Constant	1.426***	2.242***
	(9.634)	(23.359)
Zero-inflated		
Award assured (0: no, 1: yes)	-20.121***	-20.143***
	(-59.732)	(-59.836)
Constant	-2.754***	-2.770***
	(-17.521)	(-17.371)
Over-dispersion		
Constant	0.141***	0.139***
	(4.444)	(4.368)
Observations	3931	3931

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.6 Appendix F: The Magnitude Comparison

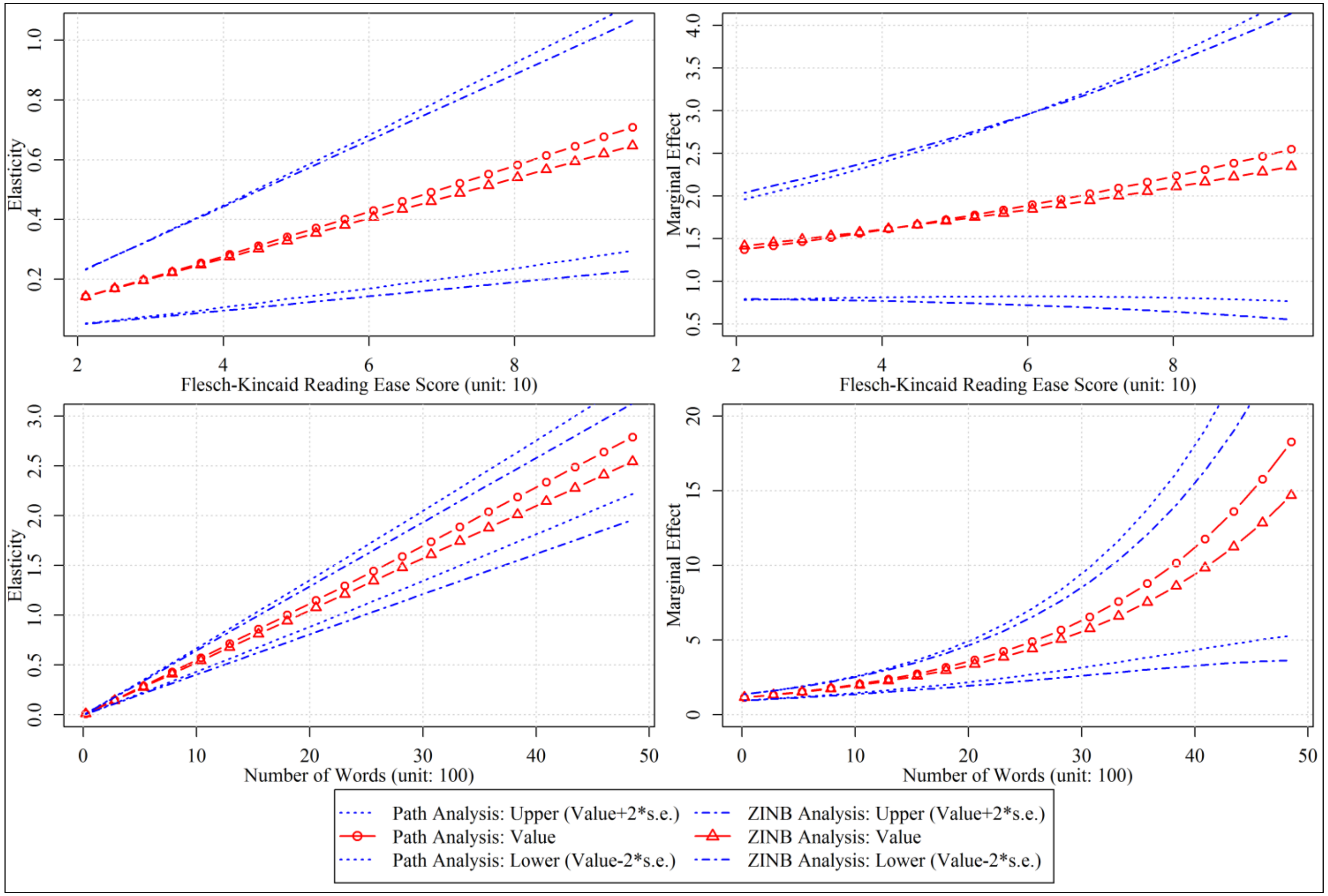


Figure 7–4 The magnitude comparison of path analysis and zero-inflated negative binominal regression

"ZINB analysis: value" represents estimated elasticities or marginal effects, and "ZINB analysis: upper" ("ZINB analysis: lower") in dotted line equals to corresponding estimated elasticities or marginal effects plus (minus) two times of their estimated standard errors.

7.7 Appendix G: The Nonlinear Effect of the Brief Length

Table 7–9 The nonlinear effect of the brief length on the contest performance

	ratio=0.11	ratio=0.13	ratio=0.15	ratio=0.17	ratio=0.19
No. High Quality Solutions					
No. High Skill Solvers (ratio in column)	0.018**	0.021***	0.021***	0.020***	0.023***
	(3.119)	(3.545)	(3.614)	(3.352)	(3.656)
No. Low Skill Solvers (ratio in column)	0.004***	0.004***	0.004***	0.004***	0.004***
	(5.667)	(5.592)	(5.795)	(6.132)	(6.068)
Flesch-Kincaid Reading Ease (unit: 10)	0.065**	0.067**	0.068**	0.067**	0.068**
	(3.030)	(3.116)	(3.143)	(3.124)	(3.161)
No. Words for Briefs (unit: 100)	0.109***	0.108***	0.109***	0.109***	0.109***
	(10.367)	(10.391)	(10.424)	(10.432)	(10.409)
No. Words for Briefs^2	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(-6.851)	(-6.880)	(-6.882)	(-6.864)	(-6.833)
No. awards (centered by 1)	0.126***	0.127***	0.128***	0.129***	0.130***
	(5.614)	(5.662)	(5.733)	(5.740)	(5.763)
Average Awards (unit: $, normalized)	0.072**	0.071**	0.072**	0.073**	0.073**
	(2.816)	(2.786)	(2.799)	(2.856)	(2.853)
Award Assured (0: no, 1: yes)	0.570***	0.581***	0.586***	0.584***	0.591***
	(14.096)	(14.172)	(14.164)	(14.042)	(14.141)
Contest duration (unit: day, normalized)	0.032	0.033	0.033	0.033	0.034
	(1.525)	(1.593)	(1.603)	(1.584)	(1.633)
category: graphic (0: web, 1: graphic)	0.388***	0.391***	0.389***	0.378***	0.373***
	(7.957)	(8.044)	(8.001)	(7.764)	(7.652)
Constant	1.171***	1.151***	1.149***	1.168***	1.165***
	(7.661)	(7.483)	(7.485)	(7.688)	(7.689)
Zero-inflated					

Award Assured (0: no, 1: yes)	-19.840***	-19.878***	-19.891***	-19.876***	-19.891***
	(-36.193)	(-37.315)	(-37.941)	(-37.459)	(-37.960)
Constant	-2.713***	-2.718***	-2.719***	-2.715***	-2.716***
	(-18.200)	(-18.137)	(-18.123)	(-18.176)	(-18.170)
Over-dispersion					
Constant	0.102***	0.102***	0.102***	0.102***	0.101***
	(3.372)	(3.363)	(3.365)	(3.365)	(3.343)
Observations	3931	3931	3931	3931	3931

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.8 Appendix H: The Nonlinear Effect of the Brief Length on the Contest Performance

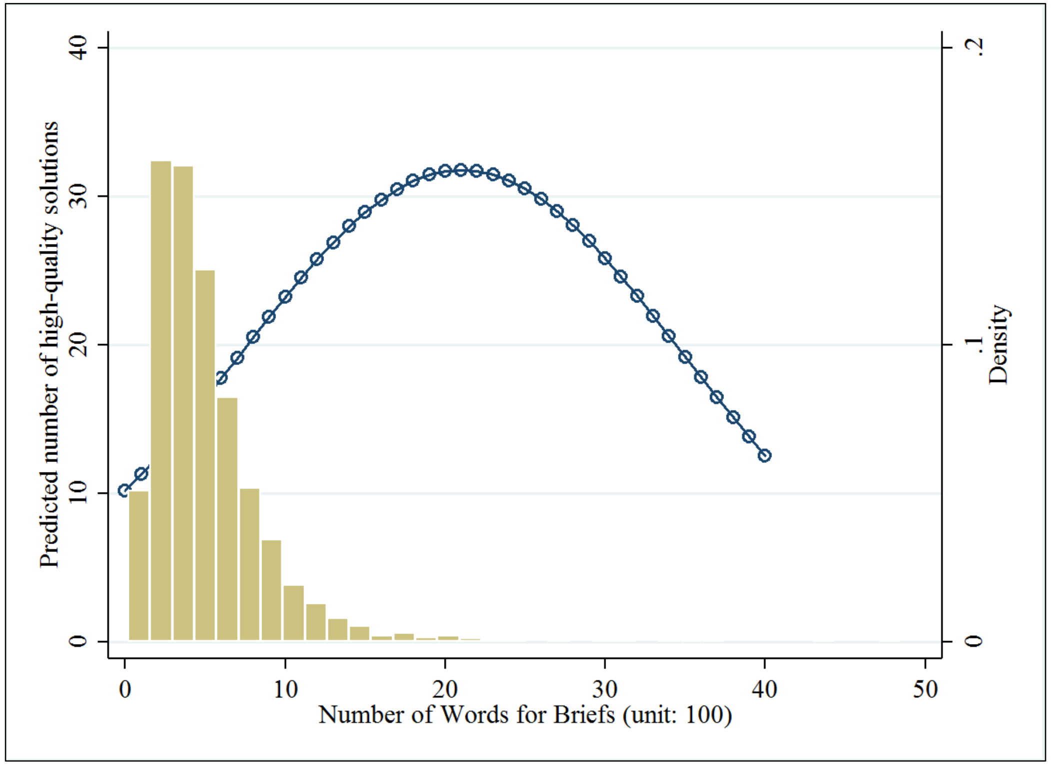


Figure 7–5 The marginal effect of the brief length (based on the ratio of 0.15)

7.9 Appendix I: Matching between Thresholds and Category of Experience

Table 7–10 The matching between 20 thresholds and the category of experience

No. submitted solutions	category of experience	No. submitted solutions	category of experience
0-22	1	359-401	11
35-68	2	402-445	12
69-103	3	446-502	13
104-137	4	503-571	14
138-172	5	572-654	15
173-206	6	655-740	16
207-241	7	741-893	17
242-277	8	894-1,105	18
278-318	9	1,106-1,476	19
319-358	10	1,477-5,686	20

Table 7–11 The matching between 30 Thresholds and the Category of experience

No. submitted solutions	category of experience	No. submitted solutions	category of experience	No. submitted solutions	category of experience
0-22	1	230-252	11	520-571	21
23-45	2	253-277	12	572-626	22
46-68	3	278-303	13	627-678	23
69-91	4	304-329	14	679-740	24
92-114	5	330-358	15	741-826	25
115-137	6	359-386	16	827-979	26
138-160	7	387-414	17	980-1105	27
161-183	8	415-445	18	1106-1281	28
184-206	9	446-483	19	1282-1705	29
207-229	10	484-519	20	1706-5686	30

Table 7–12 The Matching between 40 Thresholds and the Category of Experience

No. submitted solutions	category of experience	No. submitted solutions	category of experience	No. submitted solutions	category of experience	No. submitted solutions	category of experience
0-22	1	173-189	11	359-378	21	655-693	31
17-34	2	190-206	12	379-401	22	694-740	32
35-51	3	207-224	13	402-422	23	741-799	33
52-68	4	225-241	14	423-445	24	800-893	34
69-85	5	242-260	15	446-474	25	894-1008	35
86-103	6	261-277	16	475-502	26	1,009-1,105	36
104-120	7	278-298	17	503-527	27	1,106-1,205	37
121-137	8	299-318	18	528-571	28	1,206-1,476	38
138-154	9	319-337	19	572-612	29	1,477-2,007	39
155-172	10	338-358	20	613-654	30	2,008-5,686	40

7.10 Appendix J: Results Based on Different Experience Diversity Measures

Table 7–13 The comparison of empirical results based on different experience diversity measures

No. thresholds for definition of experience diversity	20	30	40	20	30	40
Experience	-0.064	-0.112**	-0.222***	-0.065	-0.109**	-0.219***
	(-1.387)	(-3.253)	(-5.919)	(-1.415)	(-3.152)	(-5.807)
Experience^2	-0.719***	-0.457***	-0.570***	-0.709***	-0.453***	-0.563***
	(-12.427)	(-15.781)	(-18.543)	(-11.720)	(-15.099)	(-17.564)
Uncertainty	-0.515***	-0.475***	-0.433***	-0.606***	-0.619***	-0.617***
	(-7.951)	(-7.346)	(-6.650)	(-7.719)	(-7.892)	(-8.004)
Uncertainty * Experience				0.683**	0.540***	0.669***
				(2.987)	(3.557)	(4.240)
Uncertainty * Experience^2				0.627	0.460**	0.606***
				(1.893)	(2.893)	(3.597)
No. submitted solution	0.005***	0.005***	0.006***	0.005***	0.005***	0.006***
	(21.218)	(20.181)	(20.715)	(21.336)	(20.329)	(21.046)
awards (unit: $ 1,000)	-0.484***	-0.565***	-0.598***	-0.508***	-0.587***	-0.626***
	(-4.009)	(-4.752)	(-5.110)	(-4.209)	(-4.938)	(-5.364)
Constant	2.522***	2.535***	2.503***	2.524***	2.534***	2.500***
	(77.837)	(75.483)	(72.065)	(77.967)	(75.517)	(72.066)
Over-dispersion						
Constant	-0.328***	-0.340***	-0.351***	-0.330***	-0.342***	-0.354***
	(-19.223)	(-19.669)	(-20.077)	(-19.260)	(-19.756)	(-20.235)
Observations	8,366	8,366	8,366	8,366	8,366	8,366
Cragg-Uhler R^2	0.208	0.217	0.226	0.209	0.219	0.228

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.11 Appendix K: Results of Robustness Check

Table 7–14 Empirical results for P(the submitted solution is the first solution by the solver | a solution is submitted in the contest)

Coefficients	T=1h	T=1h	T=1.5h	T=1.5h	T=2h	T=2h	T=2.5h	T=2.5h	T=3h	T=3h
Intercept	0.174***	0.192***	0.154***	0.171***	0.135***	0.150***	0.118***	0.133***	0.109***	0.122***
	(8.442)	(9.894)	(7.533)	(8.886)	(6.629)	(7.872)	(5.852)	(6.989)	(5.407)	(6.473)
dummy variable for missing information (0:	-0.928***	-0.936***	-0.907***	-0.914***	-0.886***	-0.893***	-0.868***	-0.875***	-0.857***	-0.864***
missing, 1: no missing)	(-59.737)	(-60.105)	(-59.015)	(-59.378)	(-58.271)	(-58.635)	(-57.617)	(-57.967)	(-57.387)	(-57.727)
current No. solvers	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-23.430)	(-22.921)	(-23.756)	(-23.256)	(-24.143)	(-23.656)	(-24.592)	(-24.110)	(-24.853)	(-24.383)
current No. high-quality solutions (A)	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(-12.878)	(-12.822)	(-12.342)	(-12.282)	(-11.919)	(-11.863)	(-11.429)	(-11.372)	(-11.067)	(-11.010)
current No. low-quality solutions (B)	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-11.263)	(-11.381)	(-10.703)	(-10.813)	(-10.172)	(-10.274)	(-9.619)	(-9.713)	(-9.125)	(-9.217)
No. words of problem brief (unit: 100)	-0.065***		-0.065***		-0.065***		-0.065***		-0.065***	
	(-12.735)		(-12.779)		(-12.841)		(-12.873)		(-12.913)	
average amount of awards (unit: $1,000)	0.057		0.056		0.055		0.055		0.054	
	(1.167)		(1.141)		(1.128)		(1.115)		(1.093)	
No. awards spots	-0.028*		-0.029*		-0.029*		-0.030**		-0.030**	
	(-2.422)		(-2.474)		(-2.524)		(-2.585)		(-2.621)	
contest duration (unit: day)	0.002		0.002		0.002		0.002		0.002	
	(0.761)		(0.830)		(0.918)		(1.003)		(1.051)	
assured award (Yes: 1 or No: 0)	0.055**		0.053**		0.050*		0.047*		0.045*	
	(2.724)		(2.614)		(2.490)		(2.348)		(2.249)	
Solver Level (*Variation*)	0.533	0.533	0.533	0.533	0.532	0.532	0.532	0.532	0.532	0.532
Contest Level (*Variation*)	0.105	0.119	0.104	0.118	0.104	0.118	0.104	0.118	0.104	0.119
R^2-fixed	0.068	0.065	0.067	0.064	0.066	0.063	0.065	0.062	0.064	0.062
R^2-all	0.219	0.220	0.218	0.219	0.217	0.218	0.216	0.217	0.216	0.216

Test for “A-B”	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(-8.162)	(-8.078)	(-7.845)	(-7.759)	(-7.618)	(-7.538)	(-7.341)	(-7.261)	(-7.157)	(-7.079)

Note. Column 1 to 5 differentiate with their time spending from 1 hour to 3 hours. *, **, and *** indicate statistical significance at 5%, 1%, and 0.1% levels, respectively.

Note. T values are in parentheses for fixed effects. Number of observations is 357,057. Number of solvers is 20,617. Number of contests is 1,789.

Table 7–15 Empirical results for P(the submitted solution is of high-quality by the solver | a solution is submitted in the contest)

Coefficients	T=1h	T=1h	T=1.5h	T=1.5h	T=2h	T=2h	T=2.5h	T=2.5h	T=3h	T=3h
Intercept	-3.923***	-3.611***	-3.916***	-3.603***	-3.917***	-3.603***	-3.904***	-3.590***	-3.909***	-3.594***
	(-66.001)	(-71.838)	(-65.971)	(-71.836)	(-66.171)	(-72.129)	(-66.055)	(-71.956)	(-66.032)	(-72.282)
dummy variable for missing infor-	0.243***	0.245***	0.235***	0.237***	0.235***	0.237***	0.221***	0.222***	0.225***	0.227***
mation (0: missing, 1: no missing)	(8.857)	(8.925)	(8.717)	(8.781)	(8.832)	(8.898)	(8.409)	(8.466)	(8.654)	(8.723)
current No. solvers	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(-9.772)	(-10.002)	(-9.276)	(-9.506)	(-9.036)	(-9.261)	(-8.752)	(-8.962)	(-8.544)	(-8.763)
current No. high-quality solutions by	0.104***	0.104***	0.103***	0.103***	0.102***	0.102***	0.101***	0.101***	0.100***	0.100***
the focal solver (C)	(27.588)	(27.596)	(27.100)	(27.108)	(26.546)	(26.551)	(26.110)	(26.114)	(25.753)	(25.750)
current No. high-quality solutions by	-0.006***	-0.006***	-0.006***	-0.006***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
others	(-13.882)	(-13.862)	(-14.353)	(-14.339)	(-14.651)	(-14.636)	(-14.848)	(-14.845)	(-15.056)	(-15.058)
current No. low-quality solutions by the	0.065***	0.066***	0.067***	0.067***	0.068***	0.068***	0.069***	0.069***	0.070***	0.070***
focal solver (D)	(24.458)	(24.480)	(24.848)	(24.871)	(25.066)	(25.089)	(25.350)	(25.378)	(25.409)	(25.439)
current No. low-quality solutions by	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
others (E)	(14.764)	(14.973)	(14.585)	(14.793)	(14.538)	(14.740)	(14.430)	(14.633)	(14.280)	(14.489)
No. words of problem brief (unit: 100)	0.096***		0.097***		0.098***		0.098***		0.098***	
	(4.912)		(4.938)		(4.952)		(4.972)		(4.978)	
average amount of awards (unit:	-0.569**		-0.574**		-0.577**		-0.581**		-0.583**	
$1,000)	(-2.825)		(-2.843)		(-2.848)		(-2.864)		(-2.868)	
No. awards spots	0.125**		0.125**		0.125**		0.125**		0.125**	
	(2.665)		(2.655)		(2.655)		(2.649)		(2.641)	
contest duration (unit: day)	-0.013		-0.013		-0.013		-0.013		-0.013	

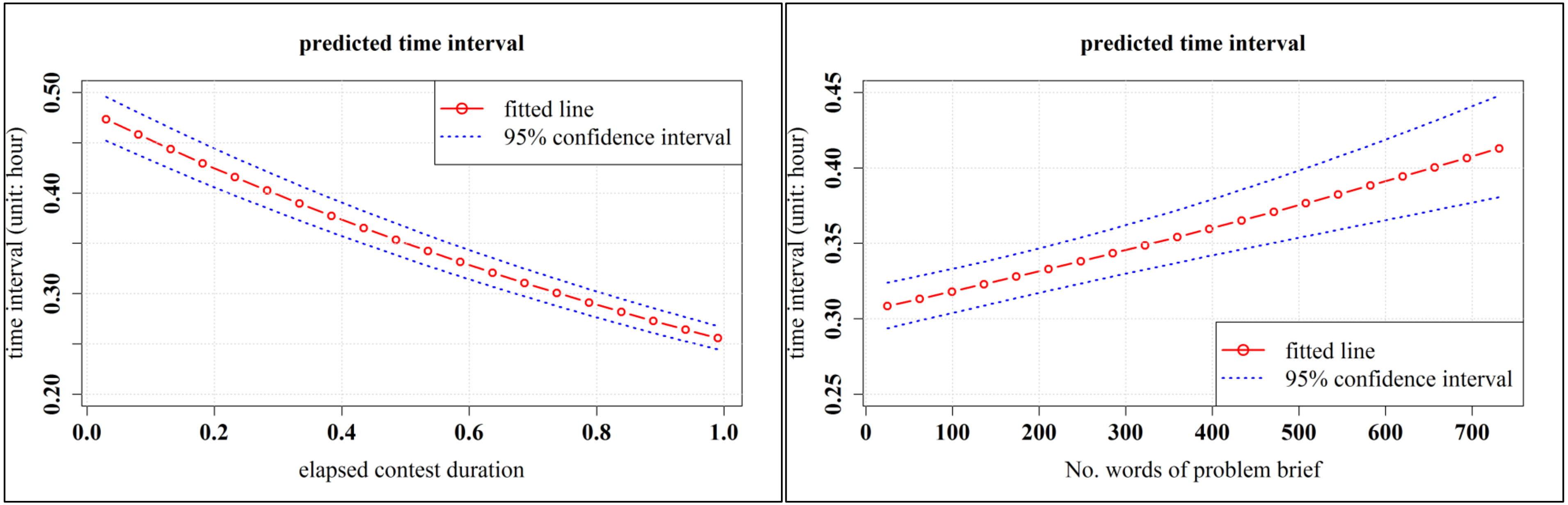
	(-1.503)		(-1.518)		(-1.533)		(-1.546)		(-1.548)	
assured award (Yes: 1 or No: 0)	0.706***		0.708***		0.709***		0.711***		0.712***	
	(9.017)		(9.022)		(9.041)		(9.050)		(9.006)	
Solver Level (*Variation*)	1.460	1.457	1.464	1.460	1.467	1.463	1.469	1.466	1.472	1.470
Contest Level (*Variation*)	2.279	2.454	2.292	2.470	2.300	2.478	2.308	2.492	2.313	2.497
R^2-fixed	0.051	0.018	0.050	0.018	0.050	0.018	0.049	0.017	0.049	0.017
R^2-all	0.556	0.552	0.556	0.552	0.557	0.553	0.557	0.554	0.558	0.554
Test for "C-D"	0.039***	0.039***	0.036***	0.036***	0.034***	0.034***	0.031***	0.031***	0.030***	0.029***
	(7.179)	(7.174)	(6.669)	(6.663)	(6.164)	(6.157)	(5.696)	(5.682)	(5.347)	(5.330)
Test for "C-E"	0.101***	0.101***	0.101***	0.101***	0.099***	0.099***	0.098***	0.098***	0.097***	0.097***
	(26.844)	(26.847)	(26.375)	(26.370)	(25.820)	(25.820)	(25.399)	(25.386)	(25.042)	(25.033)
Test for "D-E"	0.063***	0.063***	0.064***	0.064***	0.066***	0.066***	0.067***	0.067***	0.068***	0.068***
	(23.240)	(23.251)	(23.651)	(23.654)	(23.874)	(23.887)	(24.172)	(24.181)	(24.248)	(24.259)

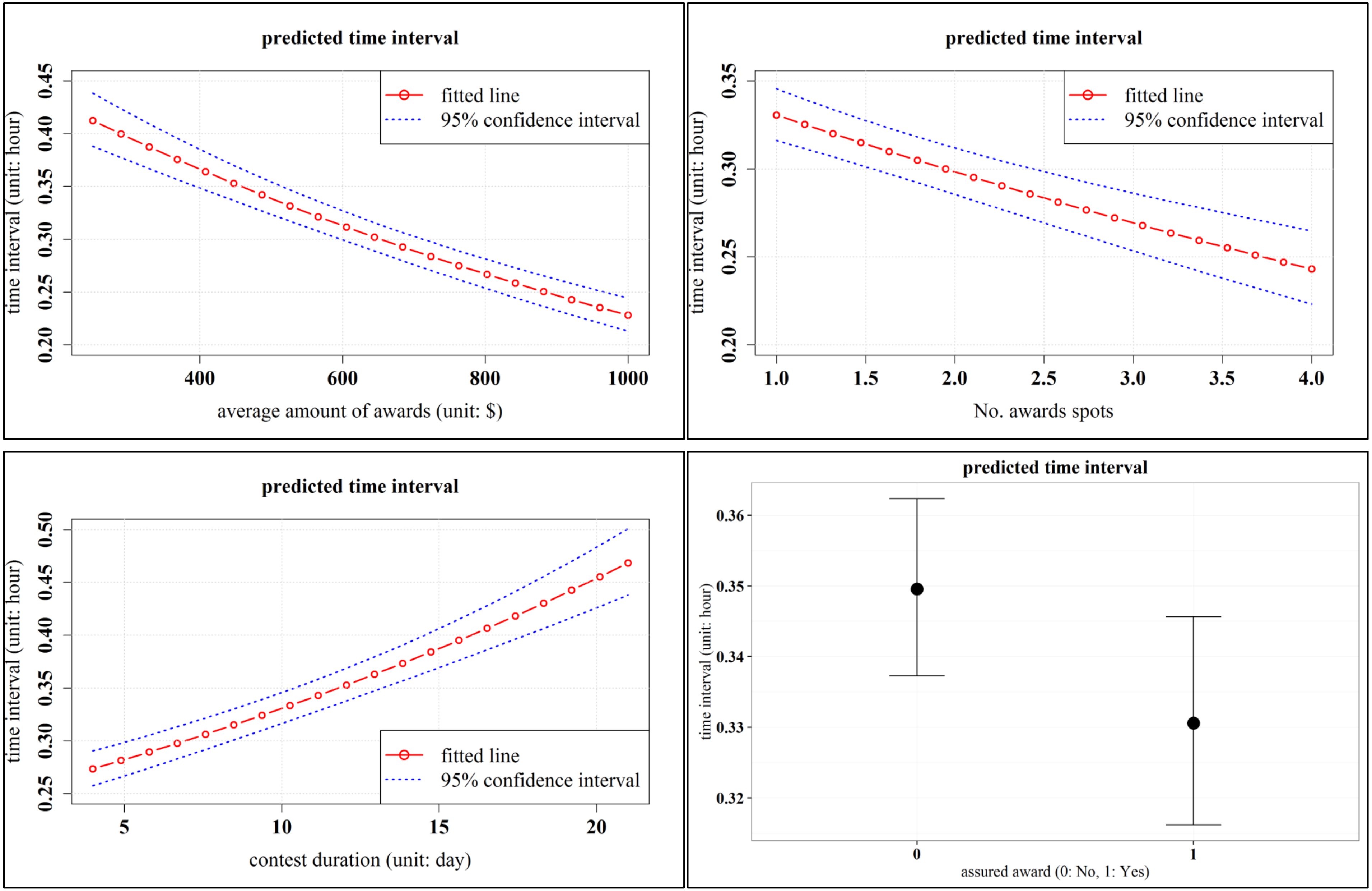
Note. Column 1 to 5 differentiate with their time spending from 1 hour to 3 hours. *, **, and *** indicate statistical significance at 5%, 1%, and 0.1% levels, respectively

Note. T values are in parentheses for fixed effects. Number of observations is 357,057. Number of solvers is 20,617. Number of contests is 1,789

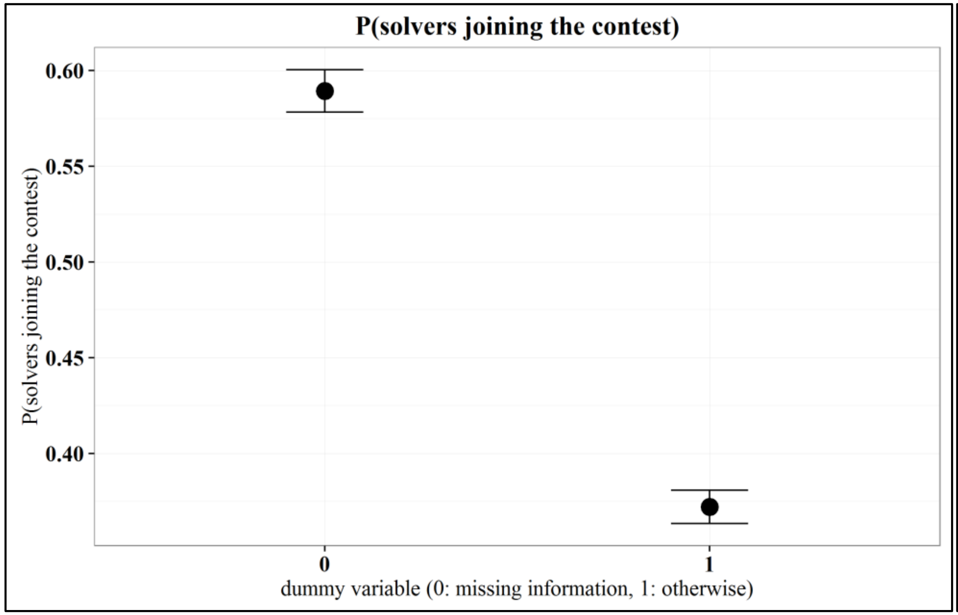
7.12 Appendix L: Marginal Effects of Independent Variables

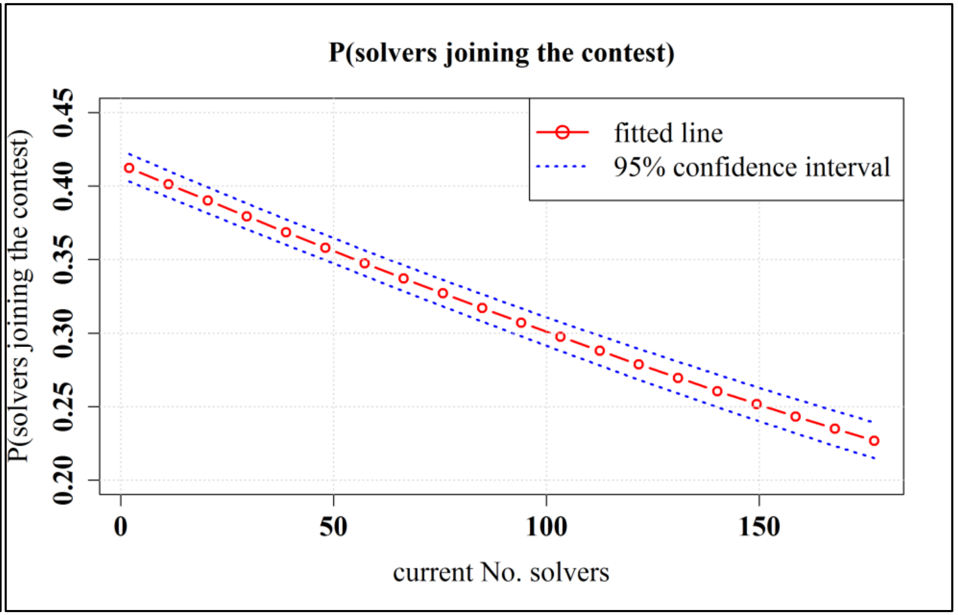
Part A: Marginal effect of independent variables in the model of time intervals between solution submitting (based on the results in Table 4–4)

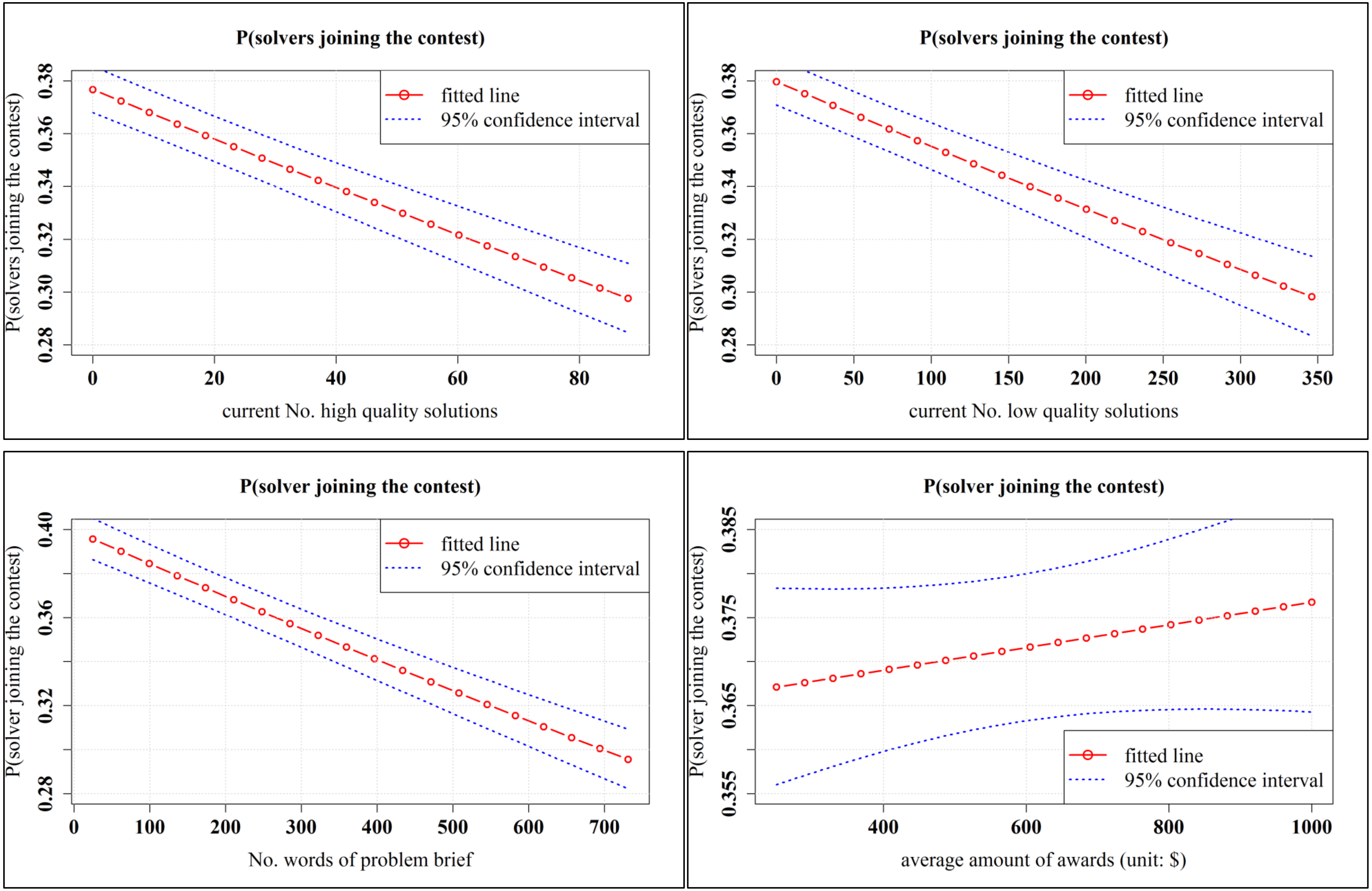


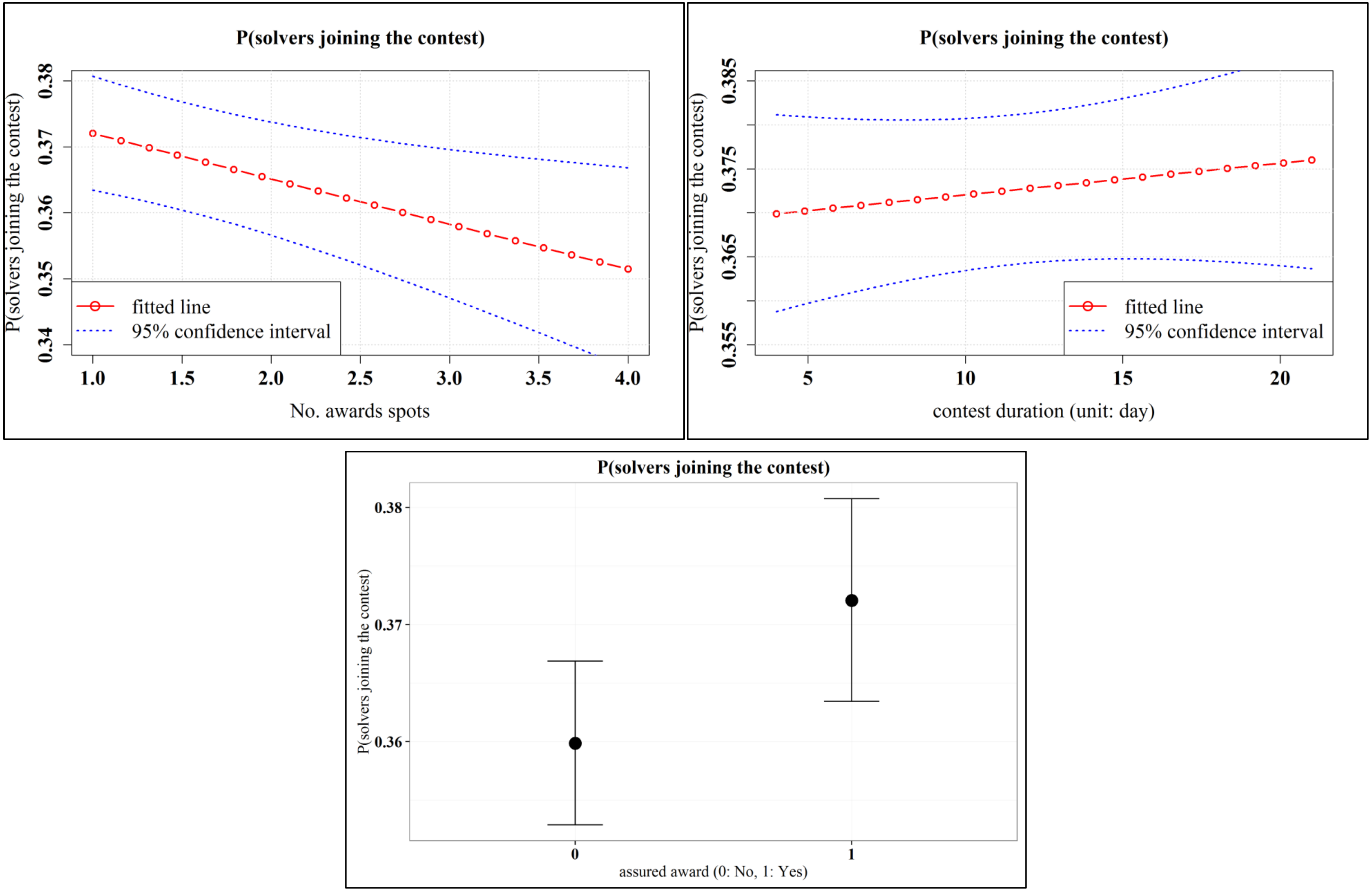

predicted time interval
time interval (unit: hour)
0.20
0.25
0.30
0.35
0.40
0.45
400
600
800
1000
average amount of awards (unit: $)
fitted line
95% confidence interval
predicted time interval
time interval (unit: hour)
0.20
0.25
0.30
0.35
1.0
1.5
2.0
2.5
3.0
3.5
4.0
No. awards spots
fitted line
95% confidence interval
predicted time interval
time interval (unit: hour)
0.25
0.30
0.35
0.40
0.45
0.50
5
10
15
20
contest duration (unit: day)
fitted line
95% confidence interval
predicted time interval
time interval (unit: hour)
0.32
0.33
0.34
0.35
0.36
0
1
assured award (0: No, 1: Yes)

Part B: Marginal effect of independent variables in the model of solvers joining the contest (based on the results in Model 2 in Table 4–5)

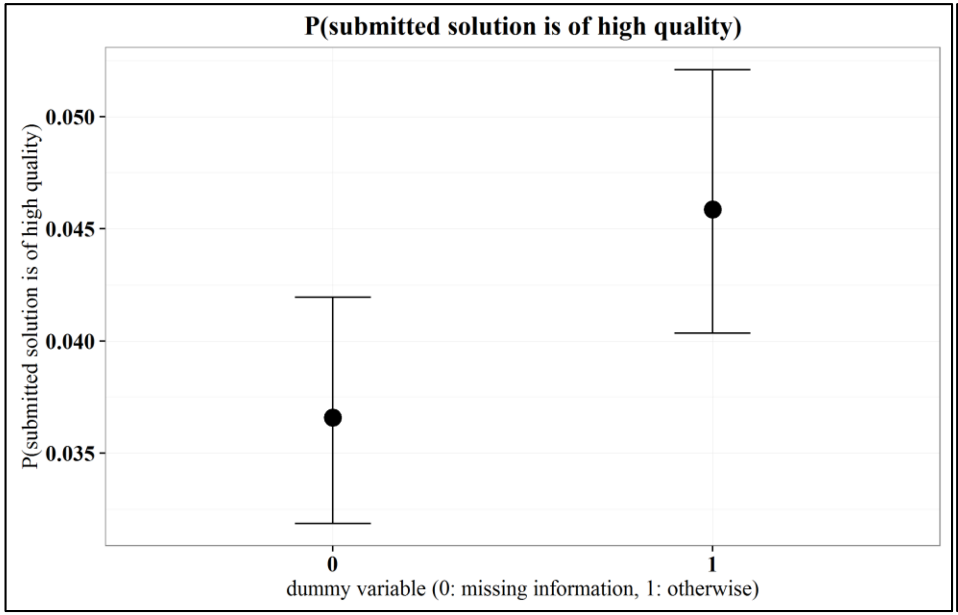


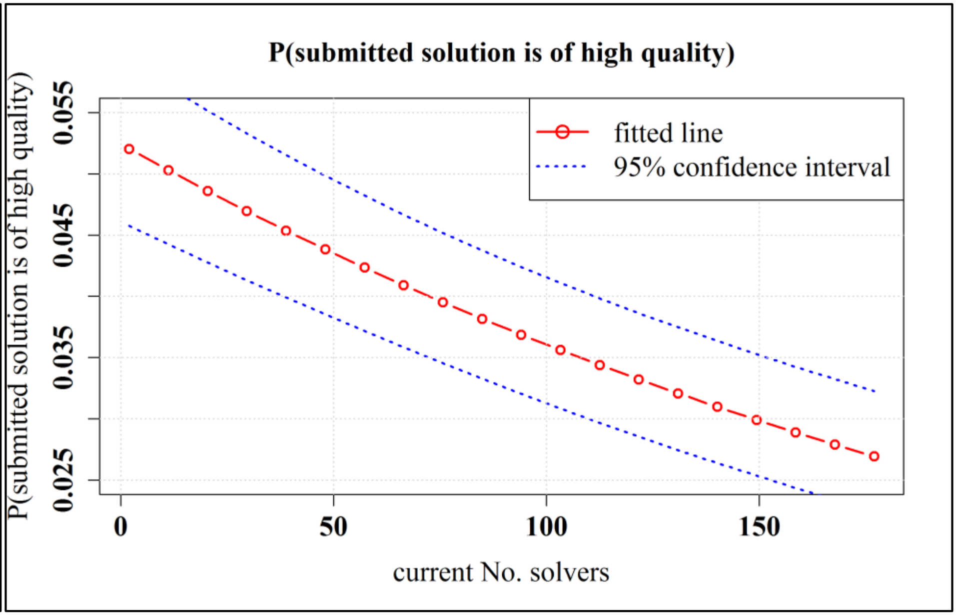


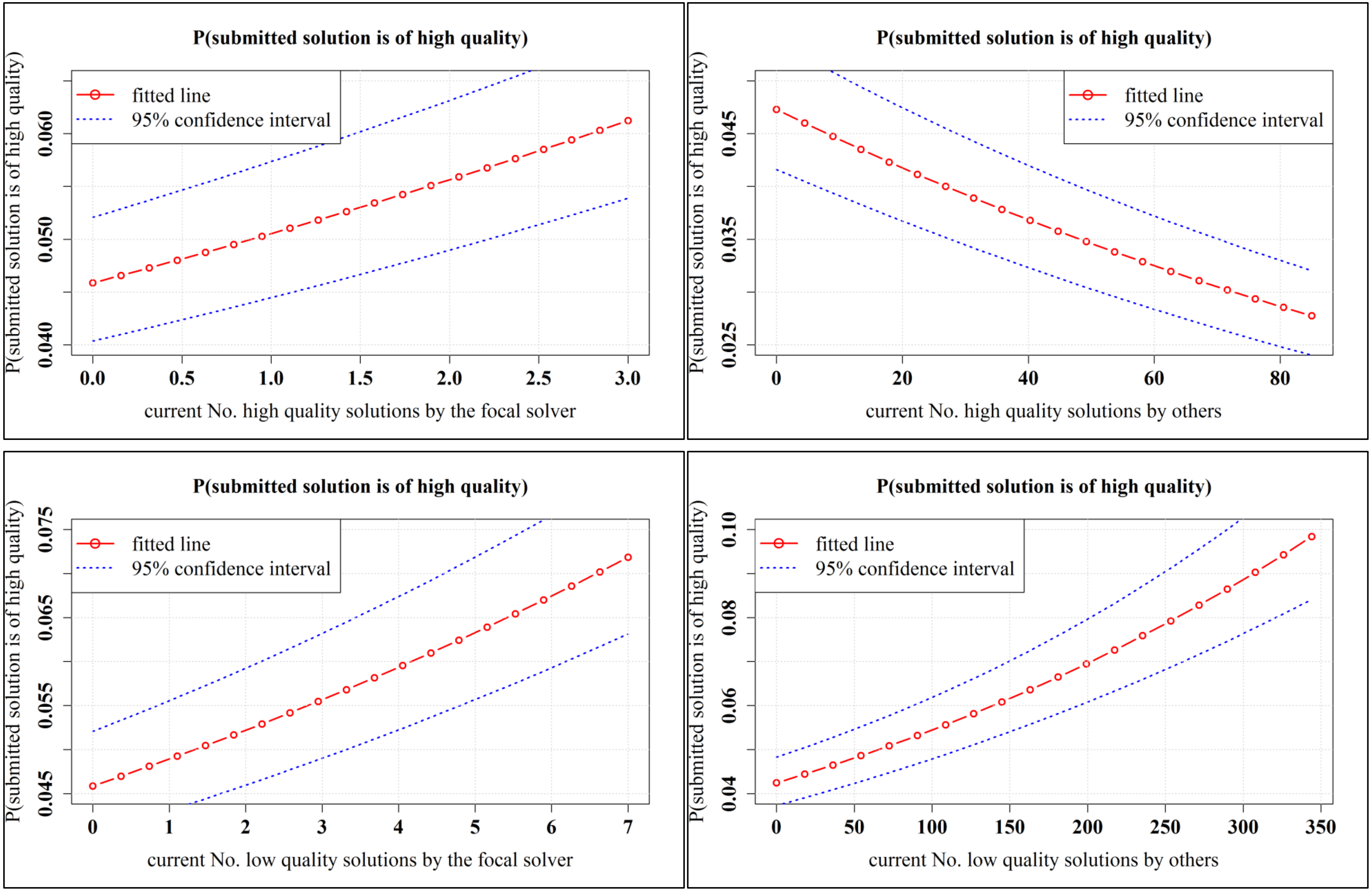

P(solvers joining the contest)
P(solvers joining the contest)
0.28
0.30
0.32
0.34
0.36
0.38
0
20
40
60
80
current No. high quality solutions
fitted line
95% confidence interval
P(solvers joining the contest)
P(solvers joining the contest)
0.28
0.30
0.32
0.34
0.36
0.38
0
50
100
150
200
250
300
350
current No. low quality solutions
fitted line
95% confidence interval
P(solver joining the contest)
P(solver joining the contest)
0.28
0.32
0.36
0.40
0
100
200
300
400
500
600
700
No. words of problem brief
fitted line
95% confidence interval
P(solver joining the contest)
P(solver joining the contest)
0.355
0.365
0.375
0.385
400
600
800
1000
average amount of awards (unit: $)
fitted line
95% confidence interval

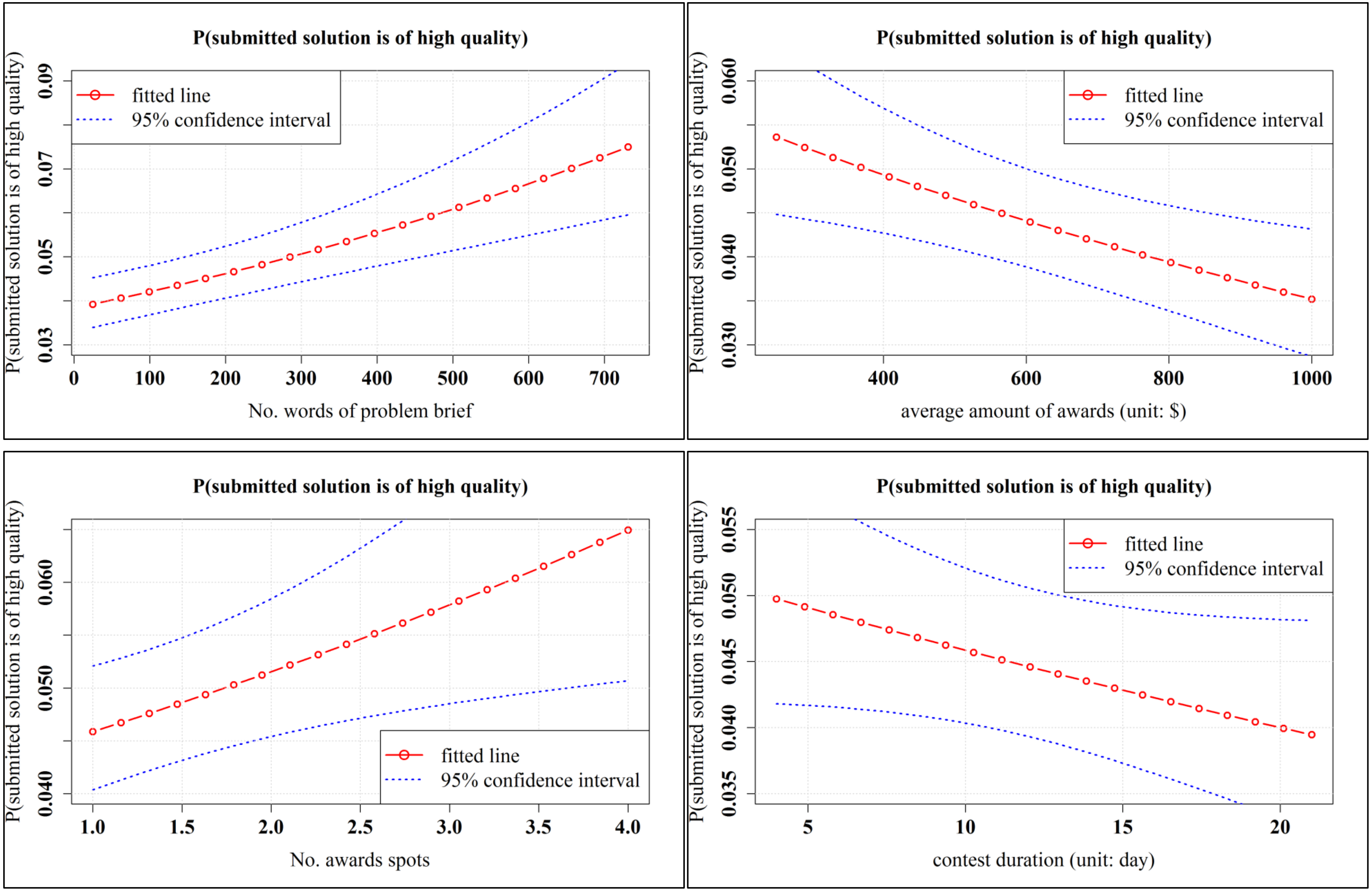

P(solvers joining the contest)
P(solvers joining the contest)
0.34
0.35
0.36
0.37
0.38
1.0
1.5
2.0
2.5
3.0
3.5
4.0
No. awards spots
fitted line
95% confidence interval
P(solvers joining the contest)
P(solvers joining the contest)
0.355
0.365
0.375
0.385
5
10
15
20
contest duration (unit: day)
fitted line
95% confidence interval
P(solvers joining the contest)
P(solvers joining the contest)
0.36
0.37
0.38
0
1
assured award (0: No, 1: Yes)

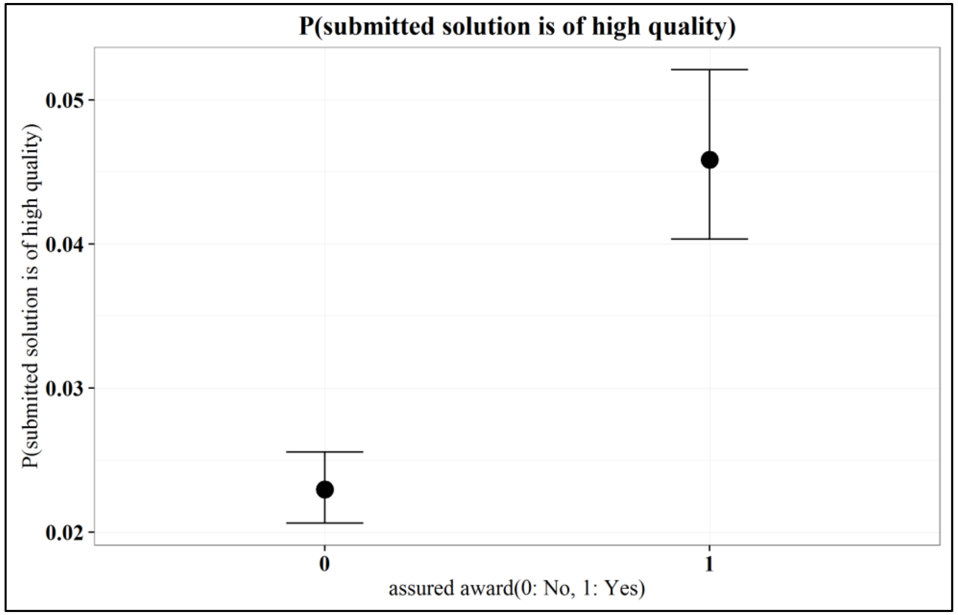
Part C: Marginal effect of independent variables in the model of solvers submitting high-quality solutions (based on the results in Model 4 in Table 4–5)






P(submitted solution is of high quality)
P(submitted solution is of high quality)
fitted line
95% confidence interval
0.040 0.050 0.060
0.0 0.5 1.0 1.5 2.0 2.5 3.0
current No. high quality solutions by the focal solver
P(submitted solution is of high quality)
P(submitted solution is of high quality)
fitted line
95% confidence interval
0.025 0.035 0.045
0 20 40 60 80
current No. high quality solutions by others
P(submitted solution is of high quality)
P(submitted solution is of high quality)
fitted line
95% confidence interval
0.045 0.055 0.065 0.075
0 1 2 3 4 5 6 7
current No. low quality solutions by the focal solver
P(submitted solution is of high quality)
P(submitted solution is of high quality)
fitted line
95% confidence interval
0.04 0.06 0.08 0.10
0 50 100 150 200 250 300 350
current No. low quality solutions by others


P(submitted solution is of high quality)
fitted line
95% confidence interval
P(submitted solution is of high quality)
0.03
0.05
0.07
0.09
0
100
200
300
400
500
600
700
No. words of problem brief
P(submitted solution is of high quality)
fitted line
95% confidence interval
P(submitted solution is of high quality)
0.030
0.040
0.050
0.060
400
600
800
1000
average amount of awards (unit: $)
P(submitted solution is of high quality)
fitted line
95% confidence interval
P(submitted solution is of high quality)
0.040
0.050
0.060
1.0
1.5
2.0
2.5
3.0
3.5
4.0
No. awards spots
P(submitted solution is of high quality)
fitted line
95% confidence interval
P(submitted solution is of high quality)
0.035
0.040
0.045
0.050
0.055
5
10
15
20
contest duration (unit: day)


P(submitted solution is of high quality)
0.05
0.04
0.03
0.02
P(submitted solution is of high quality)
0
1
assured award(0: No, 1: Yes)

8 Nederlandse Samenvatting (Summary in Dutch)

In de afgelopen jaren is sprake van een snelle stijging van het aantal bedrijven dat externe input proactief toepast om hun interne innovatieprocessen te verbeteren. Er zijn diverse manieren om bedrijven te faciliteren externe input te integreren, zoals samenwerkingsverbanden, *complementors*, arbeidsmarkten en innovatiecompetities. Innovatiecompetities kunnen worden gedefinieerd als IT-gebaseerde en tijdsbeperkte wedstrijden die door een organisatie of individu worden georganiseerd en die zich richten op het grote publiek of een specifieke doelgroep. Hierbij wordt gebruik gemaakt van hun expertise, vaardigheden of creativiteit om tot innovatieve oplossingen te komen voor een bepaalde, door de organisator vastgestelde, ingediende probleemvraag. Verschillende mechanismen zijn geschikt voor verschillende soorten innovatieproblemen. In het bijzonder zijn innovatiecompetities goed te gebruiken om duidelijk gedefinieerde, goed gestructureerde en eenvoudige problemen op te lossen.

Een typische innovatiecompetitie bij een online platform omvat de volgende stappen: een *Vraagsteller* (zoeker naar oplossingen) formuleert een probleemvraag, welke het probleem omschrijft, de vereisten voor aanvaardbare oplossingen en de prijs (prijzen) voor de beste oplossing(en). Dit wordt voorgelegd aan de *Oplossers*. Afhankelijk van hun beschikbaarheid, vaardigheden en interesses zullen sommige van de oplossers aan het probleem werken en oplossingen voorstellen aan het platform. Het platform maakt deze oplossingen beschikbaar voor de vraagsteller, en de vraagstellerscoort de oplossingen op basis van hun kwaliteit. Hoge (lage) kwaliteit oplossingen zijn de oplossingen welke (minder) waarschijnlijk zullen worden beloond. Oplossers kunnen doorgaans meerdere oplossingen indienen, en ze kunnen de scores en feedback van de vraagsteller gebruiken om hun ideeën aan te scherpen en verbeterde oplossingen opnieuw in te dienen. De stappen van indiening en feedback herhalen zich tot de competitie eindigt op een vooraf aangekondigde datum. Aan het eind van de competitie selecteert de vraagsteller één of meer oplossingen om aan de desbetreffende oplossers een prijs toe te kennen.

Aangezien innovatiecompetities vraagstellers kunnen helpen om hoogwaardige oplossingen op efficiënte wijze te verkrijgen, hebben veel grote bedrijven innovatiecompetities georganiseerd om waardevolle ideeën te genereren, waaronder Dell, Best Buy, BBC, CNN, BMW en Adobe. In lijn met de populariteit van innovatiecompetities in het bedrijfsleven, hebben academische studies zich gericht op de factoren die van invloed zijn op de resultaten van innovatiecompetities. Na een literatuurstudie concludeerden we dat competitie-ontwerpelementen (bijvoorbeeld geldprijzen en niet-geldelijke beloningen), kenmerken van de oplosser (bijvoorbeeld het aantal oplossers, demografische kenmerken) en de wijze waarop de vraagsteller competities beheert (bijvoorbeeld feedback geeft) invloed kunnen hebben op de uitkomsten van de competitie. Er zijn echter nog andere competitie-ontwerpelementen en kenmerken van de oplosser die nog onvoldoende zijn bestudeerd, maar eveneens de uitkomsten van de competitie beïnvloeden. Ten eerste is de probleemvraag van een innovatiecompetitie een belangrijke informatiebron voor oplossers. Deze wordt door de vraagsteller opgesteld en heeft mogelijk invloed op de competitie-uitkomsten. Echter, voorheen hebben studies naar innovatiecompetities meestal het effect van probleemvraag op de competitie-uitkomsten verwaarloosd en is er weinig bekend over het opstellen van probleemvraag om kwalitatief hoogwaardige oplossingen te verkrijgen.

Ten tweede, de groep oplossers is min of meer divers. Uit diversiteitsliteratuur weten we dat de diversiteit van een groep de prestaties van de groep kan beïnvloeden. Er is echter weinig bekend over het effect van diversiteit op competitie-resultaten en hoe daarmee in de praktijk kan worden omgegaan.

Ten derde behandelen de meeste innovatiecompetitie-studies innovatiewedstrijden als een wedstrijd in één ronde en wordt de onderlinge concurrentie tussen oplossers tijdens het proces van de competitie over het hoofd gezien. In sommige competities waarbij oplossers meerdere oplossingen kunnen indienen en de vraagsteller deze kan scoren, wordt interim-informatie over competitie-resultaten gegenereerd en beschikbaar gesteld aan oplossers. Dergelijke tussentijdse informatie bevat het huidige aantal oplossers die één of meer oplossingen hebben ingediend en het aantal hoog en laag scorende oplossingen. In dit geval kunnen oplossers die overwegen om een nieuwe oplossing in te dienen, worden beïnvloed door dergelijke tussentijdse informatie. Enkele studies onderzochteen het effect van tussentijdse informatie maar hun veronderstellingen zijn minder realistisch. We hebben dus maar beperkt inzicht in hoe tussentijdse informatie gegenereerd tijdens de competitie invloed heeft op de competitie-resultaten.

In dit proefschrift richten we ons op de drie bovengenoemde onderzoekleemtes. We gebruiken gegevens van een bekend online platform voor innovatiecompetities. Op basis van deze dataset bepalen we de effecten van de probleemvraag, de diversiteit van oplossers en de tussentijdse informatie over de competitie-resultaten op de competitie-resultaten in hoofdstuk 2, 3 en 4. In hoofdstuk 2 conceptualiseren en operationaliseren we de kenmerken van de probleemvraag in termen van leesbaarheid en lengte. We gaan ervan uit dat beide kenmerken van de probleemvraag invloed hebben op het aantal hoog gekwalificeerde en laag gekwalificeerde oplossers, en het aantal hoogwaardige oplossingen. Bovendien kunnen beide kenmerken indirect het aantal hoogwaardige oplossingen beïnvloeden, aangezien zowel hoog gekwalificeerde als laag gekwalificeerde oplossers oplossingen met een hoge kwaliteit kunnen indienen. We testen deze relaties met een dataset die 3.931 competities bevat, 28.325 oplossers, 591.212 ingediende oplossingen, en 319.931 scores van oplossingen. We gebruiken de Flesch Reading Ease en Flesch-Kincaid Grade Level maatstaven om de leesbaarheid van de probleemvraag te kwantificeren en het aantal woorden om de lengte van de probleemvraag te meten. De resultaten van negatieve binominale regressie, zero-inflated negatieve binominale regressie en padanalyse tonen aan dat 1) zowel de leesbaarheid als de lengte direct en indirect de resultaten van de competitie beïnvloeden, hun indirecte effecten worden bepaald door hun effecten op de aantallen hoog gekwalificeerde en laag gekwalificeerde oplossers 2) de gecombineerde effecten van beide probleemvraag kenmerken suggereren dat een competitie met een lang en gemakkelijk te lezen probleemvraag meer kwalitatief hoogwaardige oplossingen aantrekt, 3) de gecombineerde effecten van beide probleemvraag kenmerken nemen toe als de probleemvraag leesbaarder en langer wordt, en 4) zowel hoog gekwalificeerde als laag gekwalificeerde oplossers dienen oplossingen met een hoge kwaliteit in, alhoewel de kans hierop aanzienlijk groter is voor hooggekwalificeerde oplossers. Onze uitkomsten suggereren dat met de probleemvraag de vraagsteller een belangrijk middel heeft om hoog gekwalificeerde en laag gekwalificeerde oplossers aan te trekken en om de competitieresultaten te beïnvloeden.

Hoofdstuk 3 onderzoekt de gevolgen van de diversiteit in deskundigheid, land van herkomst en ervaring op de competitieresultaten en toetst het matigende effect van het onzekerheidsniveau van de probleemvraag op deze effecten. Ten eerste, op basis van het informatie-/beslissingsperspectief, veronderstellen we een omgekeerde U-vorm relatie tussen de diversiteit van oplossers binnen een competitie en de competitieresultaten. Ten tweede nemen we aan dat de manier waarop een vraagsteller de probleemvraag heeft geformuleerd, de omgekeerde U-vorm relatie kan beïnvloeden. Een probleemvraag kan worden opgesteld met behulp van meer of minder hulpwerkwoorden en bijwoorden. Op basis van de literatuur over de onzekerheidsreductie theorie stellen wij voor dat het onzekerheidsniveau van de probleemvraag de omgekeerde U-vormrelatie tussen de diversiteit en de competitieresultaten modereert. We testen de hypothesen met een dataset die 8.366 competities bevat, waarin 19.849 oplossers 916.545 oplossingen indienen en 610.332 oplossingen door de vraagstellers zijn gescoord. De empirische resultaten laten zien dat 1) diversiteit gevormd door deskundigheidsgebieden, land van herkomst en ervaring een omgekeerde U-vorm relatie heeft met het aantal hoogwaardige oplossingen, 2) een competitie met een heldere en duidelijke probleemvraag meer hoogwaardige oplossingen krijgt dan met een meer onzeker geformuleerde probleemvraag en 3) het onzekerheidsniveau van probleemvragen modereert de omgekeerde U-vormrelatie tussen diversiteit en competitieresultaten op een zodanige wijze dat, als de probleemvraag meer onzeker wordt geformuleerd, de omgekeerde U-vorm horizontaal verschuift van een kleinere naar een grotere mate van diversiteit. Uit dit onderzoek blijkt dat niet een zeer laag of zeer hoog, maar juist een enigszins gediversifieerde groep oplossers het meest bijdraagt aan betere competitieresultaten. Het matigende effect van het onzekerheidsniveau van probleemvragen suggereert dat de vraagsteller het effect van diversiteit proactief kan beïnvloeden door een probleemvraag meer of minder zeker te formuleren.

Hoofdstuk 4 onderzoekt de effecten van tussentijdse informatie op competitieresultaten. In deze studie conceptualiseren we dergelijke tussentijdse informatie als het beschikbare aantal oplossers, en het aantal laag/ en hoogwaardige oplossingen in een competitie. Laag- (of hoogwaardige) oplossingen zijn gescoorde oplossingen die minder (of meer) waarschijnlijk worden beloond door de vraagsteller wanneer de competitie voorbij is. Wij nemen aan dat de tussentijdse informatie de oplossers kan beïnvloeden die zich bij een competitie willen aansluiten en vervolgens kwalitatief hoogwaardige oplossingen zullen indienen. Op basis van voorspellingen van de motivatietheorie en het feedbackmechanisme wordt de waarschijnlijkheid dat oplossers zich zullen aansluiten bij een competitie en dat zij kwalitatief hoogwaardige oplossingen leveren functies van het beschikbare aantal oplossers, en laag scorende en hoog scorende oplossingen in de competitie. Gebaseerd op data van 1.789 competities, 20.617 oplossers en 357.057 observaties testen we deze veronderstelde relaties. Resultaten van de genormaliseerde lineaire mixed-modellen laten de volgende patronen zien. Ten eerste, er is minder kans dat een oplosser zal deelnemen aan een competitie die al meer oplossers, meer hoogwaardige oplossingen en meer laagwaardige oplossingen heeft. Ten tweede, er is een hogere kans dat een oplosser een andere hoge kwaliteit oplossing indient als deze oplosser al meer hoogwaardige oplossingen voor dezelfde competitie heeft ingediend. Ten derde is er minder kans dat een oplosser een kwalitatief hoogstaande oplossing indient als de competitie reeds veel oplossers of veel hoogwaardige oplossingen van anderen heeft. Tenslotte verhoogt de beschikbaarheid van lage kwaliteit oplossingen, ontwikkeld door of dezelfde of andere oplossers, de kans dat een oplosser een hoogwaardige oplossing indient. Uit dit onderzoek blijkt dat de toename van het aantal oplossers of hoogwaardige oplossingen een functie is van het aantal oplossers en het beschikbare aantal hoogwaardige oplossingen. Uit onze studie blijkt dat onderzoekers ook aandacht moeten schenken aan het proces van de competitie om een grondig inzicht te krijgen in innovatiecompetities, en niet alleen een competitie te behandelen als een vorm van één-ronde-wedstrijd.

Ter afsluiting, in dit proefschrift worden drie onderzoekleemtes geïdentificeerd om de competitieresultaten te verbeteren. Drie empirische studies worden uitgevoerd om deze leemtes te vullen. Het laat zien dat de probleemvraag, de diversiteit van de oplossers en de tussentijdse informatie over de competitieresultaten invloed hebben op competitieresultaten. Wij hopen dat deze bevindingen de wetenschappelijke kennis van online innovatiecompetities verrijken, toekomstig onderzoek verhelderen en een bijdrage leveren om managers betere prestaties te laten bereiken.