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The impact of fairness on the performance of crowdsourcing: an empirical analysis of two intermediate crowdsourcing platforms

Abstract

This research aims to investigate mechanisms available to the seeker to encourage participation of solvers to a challenge. We hypothesize that specific crowdsourcing mechanisms, reducing the information asymmetry of solvers on the challenge, increase solvers' perception of procedural and distributive fairness and incentive their self-selection process. Moreover, posing problem in an 'open' manner exposes seekers to possible opportunism risks. Thus, seekers utilize many safeguard contractual mechanisms to mitigate these risks and protect the information shared in a challenge. By using data from two intermediate crowdsourcing pltaforms, we provide that safeguard mechanisms may have a drawback effect; since they increase information asymmetry of participants on the execution system and the rewarding schema of a challenge, they decrease solvers' fairness and make solvers less commit. Combining previous research from the field of tournament-based crowdsourcing together with behavioural agency theory literature, this study offers important contributions, both to the theory and the practice.

Introduction

Within crowdsourcing tournaments both the seekers and solvers can be expected to have concerns about fairness. Clearly solvers favour fair treatments over unfair treatments. Moreover, seekers have a clear interest in fairness: balancing need for transparency against disclosure to competitors during innovation process (Di Gangi et al., 2010). But what does it mean to be treated fairly in a crowdsourcing contest? Are solvers who participate in a crowdsourcing system recognized and treated fairly? Different answers to these questions could be developed in behavioural agency theory (Pepper and Gore, 2015). Agency theory is important for understanding the design of fair crowdsourcing tournaments. From an agency perspective, success of crowdsourcing project originates from principles (seekers) attracting the most competent and skilled agents (solvers) (Madison et al., 2015). Thus, in contrast to the classical agency theory framework, the behavioral agency theory places agent (solvers) performance at the center of the agency model. Quirky provides a good example of how a company could attract many inventors. "*Quirky has over 1 million inventors in its community, and has developed over 400 products. Inventors can submit ideas for products, vote up ideas submitted by others and participate in the design and development of products once they have been selected to be manufactured"* (Simon, 2014). In this context, previous studies have highlighted how the wideness of the number of participants to the challenge increases the quality of the submission, the profit for the seeker and, in general, the overall performance of the challenge (Terwiesch and Xu, 2008; Jeppesen and Lakhani, 2010; Boudreau et al., 2011). In particular, having a large pool of solvers can increase the likelihood to find at least one good solution; a large set of diverse solutions mitigates and outweighs the negative effect of underinvestment of each solver (Terwiesch and Xu, 2008). This argument reflected in Gartner's recent report (2015) "*The key to successfully crowdsourcing ideas in a chaotic context is generating idea volume and engaging the community to select the best ideas for development"*. Thus, these considerations are important for managers and contest organizers who search the maximum or the best performance in a challenge (Terwiesch and Ulrich, 2009).

However, research in crowdsourcing tournaments has yet to consider the effect of inaccurate behavioural assumptions of seeker. If the seeker's behavioural assumption about solvers is inaccurate then misalignment crowdsourcing mechanism may be implemented generating unattractive crowdsourcing context. More recently, Franke et al. (2013) highlight the importance of “fairness” in a crowdsourcing contest; beyond intrinsic and extrinsic motivations, solvers also care about the allocation of resources and the power between parties. Fairness judgement can be defined by the solvers’ outcome based evaluation of seeker’s actions (Long et al. 2011). Thus, the perceived fairness of a contest can influence the individuals’ willingness to contribute in a crowdsourcing competition. Despite the importance of fairness in crowdsourcing context, a theoretical framework does not exist. Our goal in this paper is to provide such a framework. We aim to investigate how seekers can attract a large pool of solvers by designing challenges that are perceived by the solvers as fair. This vantage point allows us to examine the roles played by the seekers in designing various mechanisms to enhance the perceived fairness of organizational arrangement of the tournament-based crowdsourcing. We examine a specific form of crowdsourcing, the tournament-based form (Afuah and Tucci, 2012) in which each contributor from the crowd self-selects to work on its own solution, and the company chooses the best solution as the winning one. We conduct our empirical research by analysing a distinctive dataset of 1590 challenges collected from two intermediate ideas’ platforms (Natalicchio et al., 2014) in the spring-summer of 2014, CrowdSPRING and 99designs.

Our paper offer several contributions. First of all, we contribute to crowdsourcing literature integrating the literature on organizational justice (Gilliland 1993; Karriker and Williams, 2007) with the lietrature on tournament-based crowdsourcing (Jeppesen and Lakhani 2010; Afuah and Tucci, 2012; Franke et al., 2013) through the application of behavioural agency theory (Eisenhardt, 1989, Madison et al., 2015). Building on previous studies, we used organizational justice to describe the role of fairness as it directly relates to the crowdsourcing context (Gilliland, 1993; Franke et al., 2013). We explore the effects of fairness perceptions on behaviours of solvers that are directed at, and benefit, the success of crowdsourcing challenge. Our paper also introduces organizational justice theory to the behavioural agency model, on the basis that it shows a reasonable way of contracting between principal (seeker) and agent (solvers). Furthermore, our model includes an openness mechanism as a moderator that assists our understanding of how the risk safeguard mechanism of a seeker moderates the relationship between each of the dimensions of fairness perception of solvers and effectiveness of crowdsourcing context.

Second, past researchers in open innovation and user innovation repeatedly identified the ways in which the creative output of solvers is disclosed freely in online communities (e.g., Moorman, 1991; Franke and Shah, 2003). We began to specify the how seekers need to take into consideration the potential reaction of community members and how to deal with their perception of fair crowdsourcing process and to what extend they should disclose their technical information. Surprisingly, little research has dealt with the seeker side when designing crowdsourcing process and only one study (Franke et al., 2013) considers fairness in the crowdsourcing context. Franke et al. (2013) investigate the role of the fairness in the initial decision to contribute to a crowdsourcing system; specifically, they measure the subject's willingness to self-select and submit a design. Therefore, this is the first study which adopts a seeker's perspective to investigate the role of the fairness in the attractiveness and effectiveness of a challenge in terms of number of solvers that is self-selected and has effectively participated to solve a problem.

Third, Franke et al., (2013) used what they term "anticipatory action" as an approach to examining the predictive role of fairness perceptions exante to participations in the context of future research. They employ a simulate scenario that describes the terms and the conditions of crowdsourcing systems. As Cropanzano and Folger (1989) and Greenberg (1987) indicated, whether these simulation interactions could be generalized to real organizational setting is questionable. Considering the attractiveness of the challenge as the number of solvers that have actually participated in a challenge and submitted a solution, we study fairness perceptions *ex post* to participation rather than *ex ante*. In our work we investigate the role of fairness in attracting solvers in an actual scenario, by using secondary data gathering from existing online intermediate crowdsourcing platforms. We believe this approach spreads the external validity of our work since we collect data on real behaviours rather than intentions.

This article is organized as follows: after providing an overview of our theoretical base, we develop our hypotheses. We then describe the research methodology and present our analyses and findings. Next, we discuss the results and outline their theoretical and managerial implications. Finally, we comment on the study limitations and avenues for future research.

Theory and Hypotheses

Behavioural Agency theory has been important for understanding the design of a fair tournament-based crowdsourcing process. Pepper and Gore (2015: 1045) stated that '*behavioural agency theory places agent performance at the centre of the agency model, arguing that the interests of shareholders and their agents are most likely to be aligned if executives are motivated to perform to the best of their abilities'*. Agency perspective is relevant to situations that have a principle (seeker) – agent (solvers) structure. In this study, in the crowdsourcing context is considered such a structure as seekers delegates innovation challenges to solvers to find the best possible solutions. In a typical process of tournament-based crowdsourcing, the challenge of a company (*seeker*) is announced broadly to a crowd of outsiders (*solvers*) in form of an open call (Afuah and Tucci 2012; Spradlin, 2012). Potential participants screen the challenge and decide whether to invest in solving the challenge and submitting a solution proposal (Howe, 2006; Zhao and Zhu, 2014). The seeker then acquires the winning solution, i.e. the one that best meets pre-defined performance criteria.

Agency theory assumes that principal and agent may have different goal priorities and risks (Eisenhardt, 1989; Gefen et al., 2015). This difference between the goals of principasl and agents is described as the agency problem (Pepper and Gore, 2015; Howorth et al., 2004). Given that seeker-solver relationships have a principle-agent structure, it is important to define factors that may increase the agency problem for this relationship. We believe that in the tournament-based crowdsourcing context, two factors are important sources of conflict within the seeker-solvers relationship.

The first factor is the *lack of fairness*. The lack of proper fairness perception of the tournament-based crowdsourcing context may jeopardize crowdsourcing initiatives with the consequence of reducing the number of solvers that is self-selected and has effectively participated to solve a problem (Franke et al., 2013). As recognized by the organizational justice research, individuals' perception of the fairness affect their behaviors, such as job satisfaction, organizational commitment, performance, intention to remain with the organization (Ambrose, 2002). According to agency theory if the principal (the seeker) awards the agent (the solver) on the base of its results "*the agent will behave as the principle would like, regardless of whether his or her behaviour is monitored*" (Eisenhardt, 1989: 62). However, this might not be enough. Indeed, behavioural agency theory advises agaist the so called "inequity aversion" phenomenon (Fehr and Schmidt, 1999), that is if the solver perceives that the incentive (the award) is not fair, compared to the value the solver provides to the seeker, the solver will perceive a sense of injustice and likely he/she will not self-select for the tournment. Thus, the lack of fairness in distributing the incentive to the solver may reduce the efficency of the crowdsourcing mechanism despite the effort of the seeker to organize it. A second issue, which also deals with lack of fairness, is the lack of a clear procedure in dealing with the crowdsourcing contest. Indeed, unclear procedures increase the uncertainty the solver perceives about the possibility to actually obtain the award and, since according to behavioural agency theory (Wiseman and Gomez-Mejia, 1998; Pepper and Gore, 2015) agents are primarly loss adverse than risk adverse, this reduces the probability that solvers self select for the problem or that they actually submit a suitable idea for the problem. Thus, the presence of unclear procedures by increasing the information asymmetry between seeker and solver stresses the solvers' risk perception about possible losses reducing, in this way, the efficiency of the self-selection procedure. On the contrary, fairness process generates positive and targeted performance outcomes of crowdsourcing challenge (Karriker and Williams, 2007).

A second factor that might increases the agency problem in crowdsourcing contexts concerns *opportunism risk*. Agency theory assumes an opportunistic behavior both of the principal and the agent (Eisenhardt, 1989). In the crowdsourcing context, opportunism might cause conflict between the seeker and solvers since both tend to pursue their own interest and they are both value maximizers. As previously mentioned, the seeker could limit the conflict by designing appropriate reward system for solvers as well as transparent mechanisms. However, this would imply that seeker companies have to disclose technical problem information and/or reveal sensitive information about their future development projects (Lüttgens et al., 2014). This exposes seeker companies to possible opportunistic behaviors by the solvers (Afuah and Tucci, 2013). Such perceived risks bring seekers to design specific crowdsourcing mechanisms able to reduce the likely opportunistic behaviors from external parties. These protection mechanisms have possible drawbacks; in fact, they reduce the transparency of a challenge increasing the information asymmetry of solvers. Furthermore, risk safeguard mechanisms, defined by the seeker to protect himself form possible intellectual property abuses and confidential threats, might moderate the positive impact that the fairness has in attracting a wide range of potential solvers.

In summary, we argue that fairness, both distributive and procedural, and opportunism risk might deteriorate the agency relation between seekers and solvers in crowdsorcing context by affecting the effectiveness and the efficiency of the self-selection process.

As shown in Figure 1, incorporating these problems in the crowdsourcing context, our theoretical model extends the relationships between seeker and solvers by addressing the sources of the perceived distributive and procedural dimensions of fairness of an organizational arrangement and their corresponding attractiveness of a challenge and effectiveness. Organizational mechanism of crowdsourcing context influences the actual behaviour of solvers and subsequently the crowdsourcing outcome. We also include in our investigations the underlying question of risk safeguard mechanisms as critical parameters when designing a crowdsourcing contest.

[Figure 1, about here]

Procedural and distributive fairness

Fairness has been used extensively in organizational justice literature (Moorman, 1991; Gilliland, 1993; Karriker and Williams, 2007; Long et al., 2011) and only Franke et al., (2013) consider fairness in crowdsourcing context. They consider two dimensions of fairness; distributive and procedural. We include these two dimensions of fairness in our research to maintain comparability. *Procedural fairness* is related to the perceived justice of the process of selection (Leventhal, 1980; Lind and Tyler, 1988; Gilliand, 1993). Solvers usually desire the process to be transparent and fair, regardless of the outcome (Di Gangi et al., 2010). When a crowdsourcing process directing a particular outcome is perceived to be unfair, the solver's reactions are predicted to be directed at the seekers, rather than at his/her tasks or the specific outcome in question (Cohen-Charash and Spector, 2001). *Distributive fairness* concerns the perceived justice of outcomes of a process (Adams, 1965). Perceptions of fairness are originated in an exchange assumption: solvers assess the crowdsourcing outcomes they obtain compared with their contributions to decide whether it is a fair outcome (Lambert, 2003). When the specific outcomes of a challenge are perceived to be unfair, solvers experience an "inequity aversion" (Fehr and Schmidt, 1999) and this may influence solver's experience and ultimately their behavior (e.g. performance or withdrawal) (Cohen-Charash and Spector, 2001). In short, distributive fairness deals with the perceptions of solvers on the results of the tournament-based crowdsourcing and procedural fairness deals with perceptions of the means of crowdsourcing process (Lambert and Hogan, 2011).

According to Franke et al. (2013) in the context of tournament-based crowdsourcing the procedural fairness is formed on the basis of terms and conditions of challenge, the procedures applied to execute it, and the criteria used for selecting the winner of the prize, while the distributive fairness is formed on expectations of the participants of a fair level of reward. When a solver perceives that the challenge is unfair, both for procedural or distributive reasons, she/he does not self-select to solve that problem or does not submit any solution for that problem. For example, Di Gangi et al. (2010) show a negative reaction to perceived procedural unfairness in a Dell crowdsourcing competition. Unfair procedures can lead to reduce participation, or even to no participation at all, or migration to other crowdsourcing contests (Di Gangi and Wasko, 2009). Having a small number of competitors in a contest may decrease seeker's likelihood of finding a good and relevant solution (Boudreau et al., 2011). Thus, an unfair and non-transparent challenge is likely to have negative consequences in the overall performance of the process.

Which tools do seekers have to influence solvers' fairness perceptions? Solvers looking for contests on a crowdsourcing platform see many challenges and decide whether to join a specific challenge and submit a solution. Considering the adverse selection risk, solvers assess many challenges when choosing which ones to join on the based of available information they have on that challenge. The seeker who designed the challenge provides this information. Beyond the specific problem to solve, challenges differ among themselves mainly for the description, the information sharing allowed, the duration, the allocation of intellectual property rights, the prize amount and the prize guarantee. Seekers can devise these challenge characteristics as mechanisms to enhance perceived solvers-related fairness. In fact, some of these mechanisms, reducing the information asymmetry of the solver on the challenge, increases her/his perceived fairness and incentives the self-selection process.

For example, we reason that an award guaranteed (perception of distributive fairness) should contribute to reducing information asymmetry as experienced by the solver, or at least signal to the solver that the seeker is serious and guarantees to select a winning solver and pays out the prize at the end of the contest (Feller et al., 2012). Better understanding what seekers do, feeling assured that they will allocate equally their resources not hiding anything, should encourage solvers to self-select and submit a high quality solution for that challenge.

From a procedural perspective the solvers are also worried about transparency and non-arbitrariety of a challenge (Franke et al., 2013). Uncertainty in the procedures applied by the seeker to select the winning idea or the veto to share the solution at the end of a contest may have undesirable outcomes on the self-selection process and the quality of solvers' contributions (Nambisan, 2002; Ogawa and Piller, 2006; Di Gangi et al., 2010; Franke et al., 2013). Transparency plays a key role in reducing information asymmetry between solvers and seeker regarding the challenge to execute (Stuart et al., 2012). Sharing information about the terms and conditions of a challenge, the role that a solver plays in a contest, the procedures used to select the winning solution and the possibility to see the solution of the other solvers are all mechanisms that reduce the information asymmetry faced by the solver in tournament-based crowdsourcing. Consequently, the more information a seeker offers in designing a challenge and the more this information is transparent and open to any solvers, the lower the information asymmetry that solvers have on the challenge will be and the higher their perception will be that the seeker is designing a challenge that is procedurally fair.

Accordingly, we state the first and the second hypotheses of the paper.

H1. The perceived procedural fairness of a challenge has a positive impact on its attractiveness and effectiveness.

H2. The perceived distributive fairness of a challenge has a positive impact on its attractiveness and effectiveness.

The moderating effect of risk safeguard

This research aims to investigate tools and mechanisms available to the seeker to encourage the participation of solvers to a challenge. But in addition to tools that enhance the attractiveness and the effectiveness of a challenge, exist some mechanisms that the seekers use to mitigate some important risks.

In fact, posing problems in an ‘open’ manner exposes seekers to possible risks that reduce their ability to capture value from crowdsourcing processes (Feller et al., 2012; Afuah and Tucci, 2013). Seekers may lose control over the crowdsourced task, and the manner in which it is performed (Natalicchio et al., 2014). In addition to concerns about control and quality risks, openness may put seekers at risk of misappropriation of their ideas by solvers (Arrow, 1962; Anton and Yao, 2002). For example, solvers may reuse ideas or solutions developed for a seeker to address the needs of other clients. For a seeker, sourcing out confidential tasks (for example testing) and sensitive information inherits the risk of losing relevant know-how and may be detrimental to his/her market competitiveness (Nambisan, 2002).

Seekers utilize many safeguard contractual mechanisms to mitigate previous risks and protect their information (Nambisan and Sawhney, 2007). These contract features are designed to mitigate both pre-contractual and post-contractual potential solvers' opportunisms (Avenali et al. 2012). Typically safeguard clauses are legally binding contracts between seeker and solvers that set rules about what information is allowed to be shared and what instead has to remain undisclosed. Designing these mechanisms means seekers can control their intellectual property and protect the information shared in a challenge.

The drawback effect of safeguard mechanisms concerns the reduction of perceived fairness of solvers. The need for the seeker to mitigate opportunism risks increases the information asymmetry of solvers on the challenge (Silveira and Wright, 2010; Dushnitsky and Klueter, 2011). Mechanisms of risk safeguard since increased information asymmetry of participants on the execution system and the rewarding schema of a challenge decreases their perceived fairness and make the solvers less commital.

Thus, from the seeker perspective a tension emerges. From one hand, there are tools that reduce the information asymmetry of the solvers on the challenge, increase their perceived fairness, and incentive the self-selection process. On the other hand, seekers attempt to design the challenges to protect any proprietary material, and often impose privacy or nondisclosure policies as part of their requests. Safeguard tools tend to reduce the positive effect that perceived fairness has on challenge performance. Thus, the third hypothesis is as follows.

H3a. The impact of procedural fairness on challenge's attractiveness and effectiveness is moderated by risk safeguard mechanisms.

H3b. The impact of distributive fairness on challenge's attractiveness and effectiveness is moderated by risk safeguard mechanisms.

Data and Methods

Research Setting and Data collection

Two online intermediate crowdsourcing platforms, CrowdSPRING and 99designs, constitute the empirical setting of this paper. We choose this empirical setting for three main reasons. First of all, the characteristics of these intermediate platforms well fit with our theoretical model. In fact, since CrowdSPRING and 99design hold the number of active solver and the number of idea submitted (Sun et al.,2014) we can investigate the challenge participation. Moreover, these platforms enable the seekers to run completely open contests in which the awards are declared ex-ante and all solvers' contributes are visible to everyone (King and Lakhani, 2013). Second, CrowdSPRING and 99designs are world's largest online graphic design marketplaces focus on design tasks such as logo, business card and web design (CrowdSPRING, 2014; 99designs, 2015). CrowdSPRING groups about 170.000 creative people, 500 open projects, 5.5 million entries to date, 45.000 projects to date and 145 average entries per project. 99designs reaches more than 250,000 graphic designers from 192 countries around the world and hosts more than 370,000 design contests. Finally, we choose these two intermediate platforms since they are very similar (Wooten and Ulrich 2011), so we can built a unique dataset putting together CrowdSPRING and 99design's data challenges.

In these online intermediate crowdsourcing platforms, a seeker defines challenges through a problem statement that is publicly announced (also called a ''request for proposal'', or RFP). RFPs describe the problem to be solved and highlights the performance criteria that a winning solution has to meet. Moreover, the RFP informs potential solvers about monetary award and seekers' company name if they have decided to be disclosed. Thus, we collected secondary data from these RFPs; we analysed only closed challenges stored in platform's archives. We collected archival data in a time window of 10 months; we gathered data about 1590 closed challenges in the period between 1st January 2014 and 30th October 2014. The challenge thus represents the unity of analysis of this research. Each observation is fixed at the due date of submission and it doesn't require a study across time, thus the dataset is structured as cross-sectional.

Measures

To measure the *attractiveness* and *effectiveness* of a challenge we employ two dependent variables. The more attractive the challenge is the greater the number of solvers who want to participate by offering a solution. Therefore, we operationalize the attractiveness of the challenge measuring the total *number of active solvers* who self-select and decide to submit one or more solutions to the challenge. Moreover, an effective challenge allows the seeker to find the best graphic design for his/her needs. The probability of finding the best solution increases with the number of proposals received. Thus, we operationalize the effectiveness of a challenge measuring the difference between the number of submitted ideas and the number of ideas withdrawn by the solvers for each challenge (i.e. the *number of accepted ideas*).

Concerning explanatory variables, we operationalize the construct "procedural fairness" in terms of *solution sharing*, while the construct "distributive fairness" in terms of *award guaranteed* and *prize award*. *Solution sharing* is a mechanism through which the seeker decides whether solvers participating in the contest have the possibility to see the proposals of the other designers or not. The mechanism of solution sharing increases the transparency of the crowdsourcing system by reducing the information asymmetry between seeker and solvers. If solvers can see the proposals of the other creatives and compare these proposals with their own work, the solvers can then evaluate the system of judgment that the seeker will use in the winner's selection process, by reducing the feeling of unfairness related to favouritism and recommendations issues. For this reason we use solution sharing as a proxy of perceived procedural fairness of a challenge. Solution sharing is measured as a dichotomous variable assuming value 1 if the solver has the possibility to see the ideas submitted by other solvers during the challenge, 0 otherwise.

Another mechanism by which a seeker can characterize a challenge is the *award guaranteed*. By using this tool a seeker decides if to ensure the solvers, participating in the contest, that at least one solution will be awarded *a priori* (i.e. before knowing the solutions of solvers) or not. This means that the seeker will pay the prize even if he/she will not find a good solution among those offered by the solvers. Concerning the crowdsourcing value distribution, this condition favours almost one solver (Feller et al., 2012). For this reason we use the award guaranteed as proxy of the perceived distributive fairness of a challenge. Award guaranteed is a dichotomous variable assuming value 1 if the seeker has guaranteed that will select a winning designer and pay out the prize in the contest, 0 otherwise. Moreover, fairness theory also suggests that individuals care about the allocation of resources between parties (Franke et al., 2013). The amount of money the seeker offers as a prize, increasing the solvers' outcome, has an impact on equity perception and thus on fairness perception. In particular, the higher the prize money the greater is the likelihood that the seeker perceives the challenge as fair. This is the reason why we also use the prize award mechanism as a proxy of perceived distributive fairness. We operationalize *prize award* measuring the amount of money that the seeker assigns to winner solvers.

A *nondisclosure agreement* (NDA) is a legally binding contract between two parties that sets rules about sharing information. In the crowdsourcing context the "disclosing party" is the seeker. The seeker has important information which wishes to reveal to the "receiving party" (the solvers) but which he/shedoes not want to disclose to competitors or third parties. The NDA basically tells the solvers what information has to remain undisclosed. Through this mechanism the seeker can protect his/her information from potential solvers' opportunistic behaviours. For these reasons, we use the NDA as a proxy of seeker's risk safeguard. This measure is a dichotomous variable that assumes value 1 if the seeker and the solver agree to enter into a confidential relationship with respect to the disclosure of certain proprietary and confidential information, 0 otherwise.

We also include a number of control variables in the empirical analysis. We control when seeker reveals his/her identities to the solvers using a binary variable, *seeker identity*, that assumes the value 1 if solvers know the identity of the seeker; 0 otherwise. We also control for the effect that the *seeker typology* has on the attractiveness of a challenge. We operationalize this variable by using three dummies representing the main typology of seeker: “Firm”, “Private Seeker” and “Other Seeker type”. The *duration of challenge* indicates how long the contest is and it’s calculated as the natural alogarithm of difference between two dates, the deadline and the beginning of a challenge. Since the platform shows different type of challenge, we use four dummy variables (“Logo”, “Website & Application”, “Art, Illustration & Packaging”, “Business & Advertising”) in order to capturethe effect that the *category of challenge* has on the attractiveness. We also control for *advertising*, a binary variable that assumes a value of 1 if the challenge is advertised to the web community through newsletters or Twitter or browser pages, otherwise its value is 0. Sometimes a seeker prefers to address his/herchallenge to specific, “high-quality” solvers; we operationalize this mechanism, called *pre-selection*, as a binary variable assuming value 1 when the seeker decides to open his/her call to a small group of solvers opportunely selected, otherwise 0. Finally, we control for the effect of two platforms through a dichotomous variable, *platform*, assuming value 1 when the challenge is broadcasted on 99designs otherwise 0 (i.e. if the challenge is broadcasted on CrowdSPRING).

Model specification

We performed an in depth analysis of the data in order to select the best fitting approach for our models. Firstly, in this study the dependent variables - the number of active solvers and the number of accepted ideas - take the form of an event count variable, which has only discrete nonnegative integer values. Thus, we started evaluating the adoption of an OLS model. As shown in the histograms of Figure 2(a) and Figure 2(b), our dependent variables are strongly skewed to the right, so clearly using OLS regression would be inappropriate.

[Figure 2(a) and Figure 2(b), about here]

Moreover, since count data often follow a Poisson distribution and over-dispersion is a possible drawback with Poisson regression (Hausman et al. 1984; Cameron and Trivedi, 1998), as done in previous research we conducted some tests to assess over-dispersion in our data (Salter et al., 2015). First of all, we tested the Poisson assumption against the negative binomial model by using the goodness-of-fit (*gof*) test. The large value for chi-square in the gof test comparing the Poisson predictions for a model equivalent to model 1 in Table 3 for the dependent variable number of accepted ideas, and model 4 in Table 3 for the dependent variable number of active solvers (model 1: $\chi^2 = 41220.17$, $p = .000$; model 2: $\chi^2 = 117270.8$, $p = .000$) is an indicator that the Poisson distribution is not a good choice. We double-checked these results triangulating the gof test results with the likelihood ratio test, a test of over-dispersion parameter alpha offered in the negative binomial regression. In our case, alpha is significantly different from zero, both in model 1 (chibar2 = 6.4e+04 p =.000) and model 4 (chibar2 = 2.1e+04 p =.000), reinforcing that the Poisson distribution is not appropriate. Thus, following the results of the previous tests (gof and likelihood ratio test), we can conclude in favor of the negative binomial specification.

Second, in order to avoid unnecessary multicollinearity due to the presence of interaction terms in the models we also checked for multicollinearity problems (Aiken and West, 1991;

Salter et al., 2015). We used the variance inflation factors (VIFs) test after the regression to check for multicollinearity and we found that no variable had a VIF greater than 6, which is below the recommended ceiling of 10 (Stevens, 1992). Moreover, as suggested in Maddala and Lahiri's book (2009) we also checked this result evaluating the *t*-statistics and we found no significant unexpected shifts in the statistics caused by the inclusion and the exclusion of the variables in the models.

Finally, we computed and reported in Table 3 the likelihood ratio tests to prove the improvement of the model fit when adding independent variables (Model 2 and Model 5), interaction effects (Model 3 and Model 6) than baseline models (Model 1 and Model 3) (Gilsing et al., 2008). The log-likelihood ratio tests of Table 3 compares model 2 to model 1 and models 3 to model 2; model 5 to model 4 and model 6 to model 4.

Analysis and Results

Table 1 shows the descriptive statistics, while Table 2 provides correlations' value for all variables. The pairwise correlation matrix doesn't reveal any criticalities respects to multicollinearity problems.

[Table 1 and Table 2, abouth here]

Table 3 shows the results of the regressions. Model 1 (model 4) is the baseline model and includes only the control variables. Model 2 (model 5) introduces the independnet variables, while model 3 (model 6) evaluates the moderation hypothesis of the study.

[Table 3, about here]

Starting with the analysis on *number of active solvers* (Models from 1 to 4), model 1 includes only the control variables. We found that seeker identity is not significant. Dummy variables indicating seeker type are significant; in particular "firm" and "private" seekers have a positive effect on number of active solvers respect to "other seeker type", omitted since used as baseline category. The duration of the challenge and advertising have a significant and positive effect on number of active solvers. Dummy variables indicating the category of challenge are all significant except to "business & advertising"; in particular, "logo" challenges have a positive effect on number of active solvers while "website & application" and "art, illustration & packaging" challenges have a negative effect on number of active solvers respect to "other categories" (omitted since used as baseline category). Model 1 also shows that the mechanism of pre-selection has a negative effect on number of active solvers. Finally, the number of active solver is higher in CrowdSPRING challenges respect to 99designs challenges. In model 2, we found that the coefficient of solution sharing is significant and it has a positive effect on number of active solvers, thus supporting the first hypothesis (H1) of the paper. We also found that the coefficients of award guaranteed and prize award are significant and they have a positive effect on number of active solvers, confirming the second hypothesis (H2) of the conceptual model. To test the H3a and H3b, we consider the results of model 3. This model includes the moderator variable nondisclosure agreement (NDA) and three interaction variables. In order to avoid multicollinearity problem, variables have been standardized before performing the products. The interaction effect between NDA and solution sharing is not significant, so H3a is not confirmed. The interaction term between NDA and prize award is not significant, while the interaction between NDA and award guaranteed is significant and it has a negative coefficient, so it is possible to state that, in accordance with the formulation of H3b, the mechanism of NDA agreement negatively moderates the relationship between award guaranteed and number of active solvers.

Considering the results on *number of accepted ideas* (table 3, from model 4 to model 6), model 4 includes only the control variables. The results of model 4 (significance and signs of the coefficients) are equal to the results of model 1. Then the considerations made about controls' effect on number of active solvers can be extended to the number of accepted ideas. The coefficient solution sharing is significant and it has a positive effect on challenge effectiveness indicating that, as stated in hypothesys 1 (H1), the mechanism of solution sharing increases the number of accepted ideas. Since the coefficients of award guaranteed and prize award are significant and they have a positive effect on number of accepted ideas, hypothesis 2 (H2) is also supported. This means that mechanisms of award guaranteed and the amount of prize award increase the number of accepted ideas. Finally, model 6 tests H3a and H3b. The interaction effect between NDA and solution sharing is not significant, so also for number of accepted ideas the H3a is not confirmed. Moreover, also in this case the interaction term between NDA and prize award is not significant, while the interaction between NDA and award guaranteed is significant and it has a negative coefficient, meaning that the mechanism of NDA negatively moderates the relationship between award guaranteed and number of accepted ideas (H3b confirmed).

In addition, as also suggested by Jaccard and Turrisi (2003), we provided an even more interesting insights on the magnitude of the moderation effects carrying out a graphical analyis whose results are reported in Figure 3(a) and 3(b). Figure 3a plots the effect of the interaction on predicted values of number of active solvers of NDA and award guaranteed. The dot line shows the slope of the effect of award guaranteed on number of active solvers when the value of NDA is set equal to zero, while the continuus line shows the slope of the effect of award guaranteed on number of active solvers when the value of NDA is set equal to one (Shilling and Phelps, 2007; Mazzola et al., 2015). Consistent with the results in model 3

Table 3, the presence of NDA decreases the positive effect of award guaranteed on number of active solvers. Figure 3b plots the effect of the interaction on predicted values of number of accepted ideas of NDA and award guaranteed. Also in this plot, the dot line shows the slope of the effect of award guaranteed on number of accepted ideas when the value of NDA is set equal to zero, while the continuus line shows the slope of the effect of award guaranteed on number of accepted ideas when the value of NDA is set equal to one. Consistent with the results in model 6, the presence of NDA decreases the positive effect of award guaranteed on number of accepted ideas.

[Figure 3(a) and Figure 3(b), about here]

Discussion and Conclusions

Recent research in crowdsourcing fails to find much relevance of agency theory to explain the seeker and solver relationship. This study examined the influence of the agency theory in crowdsourcing companies and the solvers relationshipwith the fairness strategy. In addition, we examined the association between fairness strategy and effectivess and attractiveness of crowdsourcing contest. As evident from previous studies (Terwiesch and Xu, 2008; Boudreau et al., 2011), attracting a large pool of participants in a contest is seen to be strategically important. Thus, in this study we explain how seekers attract a large pool of solvers by designing challenges that are perceived by the solvers as fair. Extending behavioral agency theory to the seeker and solver relationship in a tornument-based crowdosurcing context, we framed hypotheses relating the two factors that are sources of conflict within seeker and solver relationship. We used behavioral agency theory on the relationship between perceived fairness of crowdsourcing and performance, using attractiveness of the tournament and effectiveness as yardsticks. Analysing detailed data from 1590 challenges, we found the following results as follows: 1) the challenge attractiveness and effectiveness increases as the perceived procedural and distributive fairness is designed in response to agency problems; 2) risk safegurd mechanism moderates the relationship between the distributive fairness and attractivenss and effiency of challenge; 3) no importance is given to risk safegurd mechanism of crowdsourcing when the solvers consider perceived procedural fairness is in place and associated with attractiveness of crowdsourcing.

Our results provide moderate support for the application of behavirol agency theory to fairness strategy within the seeker and solver relationship during tournament-based crowdsourcing. Neverthless, the results also indicate that the agency problem in crowdsourcing context is multidimentional, different aspects of the problems influencing the different fairness components.

Procedural and distributive fairness and attractiveness of crowdsourcing were considered important for understanding the degree to which the agency problem may exist for a seeker-solver relationship. We said that these variables reveal the extent of information asymmetry between seeker and solvers resulting from high level of information sharing about the terms and conditions of a challenge. Furthermore, the possibility to see and share the solution of the other solvers increases the trust of solvers on the challenge and increases the number of accepted ideas. Through these results we found confirmation that mechanisms as the award guaranteed, by signalling to the solver that the seeker is reliable and that she/he will effectively select a winning solution and pay out the prize at the end of the contest, enlarge the number of competitors of a challenge and the number of accepted ideas. Furthermore, the amounty of prize was to found have a strong impact on perceived level of equity. The fair perception that explain much of our research emphasizes that procedure descrease solvers' concerns with reward distributions or crowdsourcing effectiveness. Therefore, managers should not only concern endorsing fair procedures but also consider rewards are equitably allocated (Kim and Mauborgne, 1997). In line with behavioral agency theory (Pepper and Gore, 2015) our results indicate that solvers will perform well in the crowdsourcing context if they have ability (the necesary knowledge, skills etc.), the motivation (i.e., rewards etc.) and the fair mechanism (including the transparent online platform and environment).

The results regarding the risk safeguard mechanism are not straighforward. As predicted in agency arguments, increased the impact of distributive fairness on challenge's attractiveness and effectiveness is moderated by risk safeguard mechanisms. The results indicate that designing a challenge with strong policies of risk safeguard worsens the benefit that the award guaranteed has in attracting a large pool of participants and a large amount of accepted ideas. Moreover, we did not find empirically confirmation about the same moderator effect that safeguard mechanisms have on the relation between procedural fairness and challenge performance. It seems that signing an NDA does not affect the positive effect that solution sharing has on challenge performance. Hence, the underlying question of risk safeguard mechanisms is a crucial parameter in the design of contests. This result is line with Cohen-charash and Spector (2001: 280) research, "*solvers create their procedural fairness judgments with regard to their beliefs of how the systems or procedures "should" operate"*. Why is there only partial support for the moderation affect of risk safeguard mechanism? It may be that the answer to it lies in the colloborative relations between procedural and distributive fairness, as were documented in the fairness literature (Greenberg 1987; Leventhal, 1990).

Our study offers important contributions to the research on tournament-based crowdsourcing. Contraray from previous studies that basically take a solver's perspective in explaining the challenge performance, we adopt the seeker's perspective. We suggest that seekers should effectively design the knowledge creation process in a crowdsourcing contest by maintaining high levels of solvers' motivation and fairness perception during the challenge. In fact, despite the great part of a crowdsourcing task is done outside of the seeker company, the seeker has to dedicate resources and should not neglect its efforts through all the process. Doing so seeker may result in successful crowdsourcing experiences.

Furthermore, we evaluate fairness perception through an *ex post* analysis rather than an *ex ante* judgment. In particular, we measure the attractiveness of the challenge as the number of solvers that has actually participated in that challenge and has actually submitted an idea. In this sense, the willingness to submit of Franke et al. (2013) can be viewed as an antecedent of the attractiveness of a challenge, because in our *ex post* analysis procedural and distributive fairness are actually experienced by the solvers and not only anticipated.

Finally, we test our theoretical framework by using archival data. Besides the typical limitations of archival data, these are objective numbers and tell exactly how the crowdsourcing system behaves. Differently to previous empirical studies on tournament-based crowdsourcing (Terwiesch and Xu, 2008; Franke et al., 2013), since archival data are not subjective and there is no experimenter imposed bias on them, we are able to investigate the role of fairness in attracting solvers in a real setting with real players that invest real money and real effort. Hence using data on actual behaviours rather than simulated actions and/or intentions enriches external validity of our results.

Our results have also important practical implications for managers organizing a crowdsourcing contest. Managers need to be aware of the perceived fairness that seekers have about a contest. For example, the commitment to a transparent crowdsourcing process increases the perceptions of procedural fairness. This warranty can be achieved by including solution sharing clauses when designing a challenge. When solvers can see the proposed solutions of the other solvers and compare these with their own ideas, they can then evaluate the system of judgment that seeker will use in the winners selection process, by increasing the overall perception of a fair challenge. An additional implication is that to attract solvers and quality solutions managers might do well to design specific reward mechanisms that create a sense of justice about the resource allocation between seeker and solvers. At the same time, our findings on the role of risk safeguard mechanisms in moderating the fairness and challenge performance relation highlight the essential role that managers play in designing a contest. In particular, when design a challenge managers have to carefully balance levels of transparency with risk safeguard policies needed to mitigate possible opportunistic behaviours. This means finding a trade-off between designing a challenge perceived as fair and designing a challenge in order to protect intellectual property.

Future Research

Several opportunities for future research in fairness perception of crowdsourcing emerge. One possibility would be to examine a causal relationship between procedural fairness and distributive fairness. For example, Leventhal (1980) proposed that percieved procedural fairness affected consequence perception of distributive fairness. As he stated that *'... such evaluations affect the perceived fairness of the final distribution of reward. If the procedures are seen as fair, then the final distribution is likely to be accepted as fair even though it may be disadvantageous*, (p. 36)'. The future research should continue to examine the fairness aspects in crowdsourcing context, paying thoughful consideration to issues of fairness source, and their interactions not only from solver's perspective but also seeker's perspective. The fact that behavioral agency theorist have started considering the importance of the agent's work motivation, including intrinsic and extrinsic motivation in the principle and agent relationship (Pepper and Gore, 2015). Specifically, future research in crowdsourcing should benefit from inclusion the relationship between motivation of solvers and perception of their fairness of the system, when the fairness and efficiency and attractivess of the crowdsourcing construct is applied, so that each of the fairness dimensions has a focal counterpart. Once these measurements considered, further attention to new mediators and moderators of fairness and success of crowdsourcing should be explored.

Other outcome variables, including those representing performance and success of tournemant-based crowdsourcing, may be considered. These success variables might include individual (solvers, managers of crowdosurcing company) and company-level as well as comminuty level of outcomes.

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TABLES

Variables	Mean	SD	Min	Max
Number of active solvers	30.11	42.96	1	1078
Number of accepted ideas	69.59	98.23	0	2559
Seeker identity	0.98	0.14	0	1
Seeker typology				
Firm	0.63	0.48	0	1
Private	0.12	0.32	0	1
Other Seeker Type	0.25	0.44	0	1
Duration of the challenge	2.05	0.55	0	6.81
Challenge category				
Logo	0.73	0.44	0	1
Website & Application	0.10	0.30	0	1
Art, Illustration & Packaging	0.06	0.24	0	1
Business & Advertising	0.77	0.27	0	1
Other challenge categories	0.03	0.17	0	1
Advertising	0.31	0.46	0	1
Pre-selection	0.02	0.14	0	1
Platform	0.48	0.50	0	1
Solution Sharing	0.83	0.37	0	1
Award Guaranteed	0.79	0.41	0	1
Price Award	325.48	249.51	0	1
NDA	0.10	0.30	0	3503

Table 1. Descriptive statistics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Number of active solvers	1.00										
(2) Number of accepted ideas	0.93	1.00									
(3) Seeker identity	-0.03	-0.03	1.00								
(4) Firm	0.07	0.06	0.01	1.00							
(5) Private	-0.05	-0.04	-0.03	-0.47	1.00						
(6) Other Seeker Type	-0.05	-0.04	0.02	-0.76	-0.21	1.00					
(7) Duration of the challenge	-0.08	-0.03	0.06	-0.08	0.09	0.03	1.00				
(8) Logo	0.21	0.14	-0.01	-0.06	0.05	0.03	0.003	1.00			
(9) Website & Application	-0.12	-0.09	0.001	0.001	-0.06	0.04	0.09	-0.55	1.00		
(10) Art, Illustration & Packaging	-0.09	-0.06	-0.001	0.08	-0.04	-0.06	-0.04	-0.42	-0.09	1.00	
(11) Business & Advertising	-0.10	-0.07	0.02	0.07	-0.06	-0.03	-0.04	-0.48	-0.10	-0.07	1.00
(12) Other challenge categories	-0.04	-0.01	-0.001	-0.05	0.11	-0.02	-0.03	-0.29	-0.06	-0.05	-0.05
(13) Advertising	0.02	0.07	-0.004	-0.02	0.01	0.01	0.19	-0.03	0.06	0.02	0.0004
(14) Pre-selection	-0.03	-0.03	0.02	0.02	-0.04	0.001	-0.05	0.01	0.04	-0.02	-0.04
(15) Platform	-0.25	-0.18	0.09	-0.13	0.18	0.01	0.61	0.11	-0.03	-0.07	-0.03
(16) Solution Sharing	-0.01	-0.01	0.05	-0.05	0.08	-0.004	0.15	0.32	-0.36	-0.09	-0.05
(17) Award Guaranteed	0.14	0.15	-0.05	0.01	-0.08	0.05	-0.18	-0.05	-0.001	0.05	0.03
(18) Price Award	0.16	0.21	0.02	0.05	-0.09	0.01	0.12	-0.28	0.45	0.02	-0.03
(19) Nondisclosure Agreement	0.15	0.17	-0.07	0.03	-0.09	0.03	-0.17	-0.07	0.07	0.02	0.02

Variables	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(13) Advertising	-0.04	1.00						
(14) Pre-selection	-0.03	0.03	1.00					
(15) Platform	-0.08	0.29	-0.09	1.00				
(16) Solution Sharing	-0.02	0.08	-0.07	0.43	1.00			
(17) Award Guaranteed	0.02	-0.03	0.02	-0.37	-0.20	1.00		
(18) Price Award	-0.05	0.20	0.32	-0.05	-0.27	0.06	1.00	
(19) Nondisclosure Agreement	0.03	0.45	0.11	-0.30	-0.20	0.11	0.17	1.00

Table 2. Correlation matrix

	Number of active solvers			Number of accepted ideas		
	M1	*M2*	*M3*	*M4*	*M5*	*M6*
Seeker identity	0.004	-0.004	-0.017	-0.089	-0.058	-0.060
	(0.119)	(0.107)	(0.106)	(0.132)	(0.118)	(0.118)
Firm	0.151***	0.128***	0.129***	0.100*	0.087*	-0.086*
	(0.039)	(0.035)	(0.035)	(0.043)	(0.039)	(0.039)
Private	0.135*	0.182***	0.182***	0.054	0.093	0.093
	(0.061)	(0.054)	(0.054)	(0.067)	(0.060)	(0.060)
Duration of the challenge	0.325***	0.206***	0.204***	0.387***	0.227***	0.224***
	(0.039)	(0.035)	(0.035)	(0.046)	(0.041)	(0.041)
Logo	0.693***	0.642***	0.629***	0.318**	0.258**	0.257**
	(0.099)	(0.089)	(0.089)	(0.108)	(0.097)	(0.097)
Website & Application	-0.240*	-0.556***	-0.573***	-0.333**	-0.638***	-0.640***
	(0.112)	(0.105)	(0.104)	(0.122)	(0.112)	(0.112)
Art, Illustration & Packaging	-0.310**	-0.383***	-0.397***	-0.299*	-0.419***	-0.428***
	(0.120)	(0.108)	(0.108)	(0.130)	(0.116)	(0.116)
Business & Advertising	-0.134	-0.184*	-0.208*	-0.129	-0.224*	-0.235*
	(0.116)	(0.105)	(0.104)	(0.126)	(0.113)	(0.112)
Advertising	0.335***	0.139***	0.173***	0.418***	0.214***	0.200***
	(0.038)	(0.036)	(0.044)	(0.042)	(0.039)	(0.047)
Pre-selection	-0.640***	-1.173***	-1.190***	-0.490***	-0.970***	-1.041***
	(0.122)	(0.117)	(0.116)	(0.133)	(0.124)	(0.126)
Platform	-1.070***	-0.945***	-0.959***	-0.903***	-0.726***	-0.712***
	(0.045)	(0.046)	(0.049)	(0.050)	(0.052)	(0.055)
Solution Sharing		0.281***	0.266***		0.268***	0.259***
		(0.047)	(0.048)		(0.051)	(0.052)
Award Guaranteed		0.300***	0.269***		0.382***	0.355***
		(0.040)	(0.041)		(0.043)	(0.045)
Price Award		0.001***	0.001***		0.001***	0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
NDA			-0.013			0.122
			(0.073)			(0.081)
Solution Sharing*NDA			0.002			0.004
			(0.012)			(0.013)
Award Guaranteed*NDA			-0.078***			-0.074**
			(0.023)			(0.026)
Prize Award*NDA			0.002			-0.013
			(0.013)			(0.014)
Cons	2.435	1.818	1.883	3.519	2.843	2.862
	(0.170)	(0.162)	(0.164)	(0.190)	(0.180)	(0.182)
Observations	1590	1590	1590	1590	1590	1590
Pseudo R2	0.0645	0.0911	0.0922	0.0295	0.0523	0.0530
Log-likelihood	-6516.06	-6331.10	-6319.30	-8035.53	-7846.85	-7836.06
Chi-square test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log-likelihood ratio test	-	2.01*	2.89*	-	2.13*	2.99*

Table 3. Negative binomial results

FIGURES

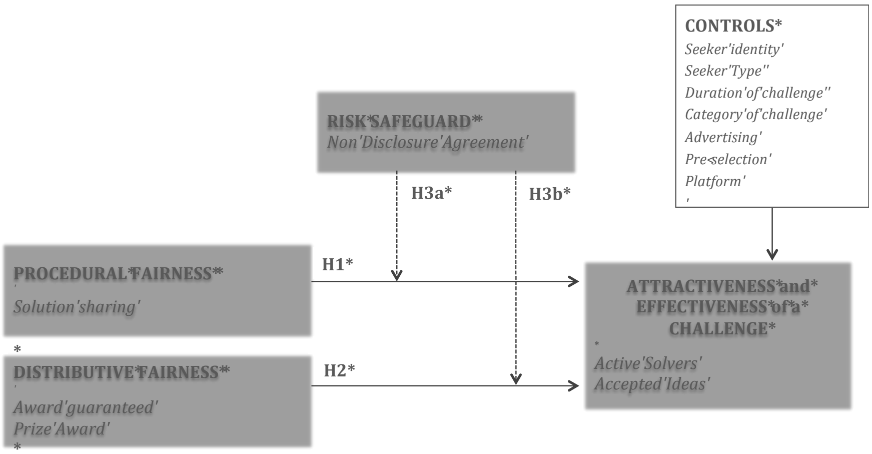

Figure 1. Conceptual Model.

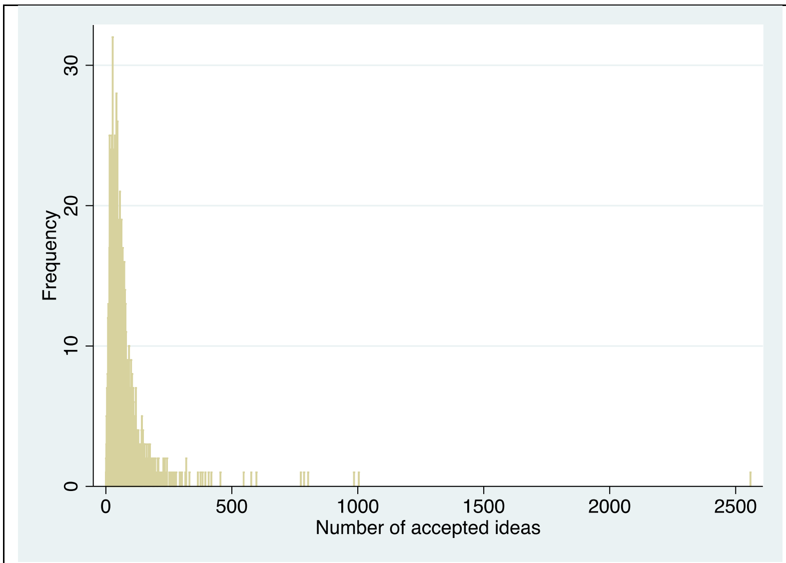

Figure 2(a). Number of accepted ideas variable distribution.

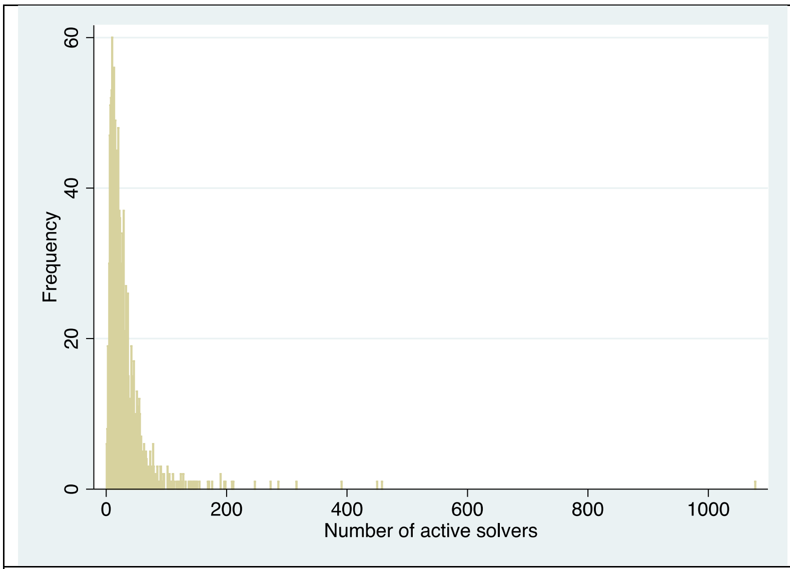

Figure 2(b). Number of active solvers variable distrubution.

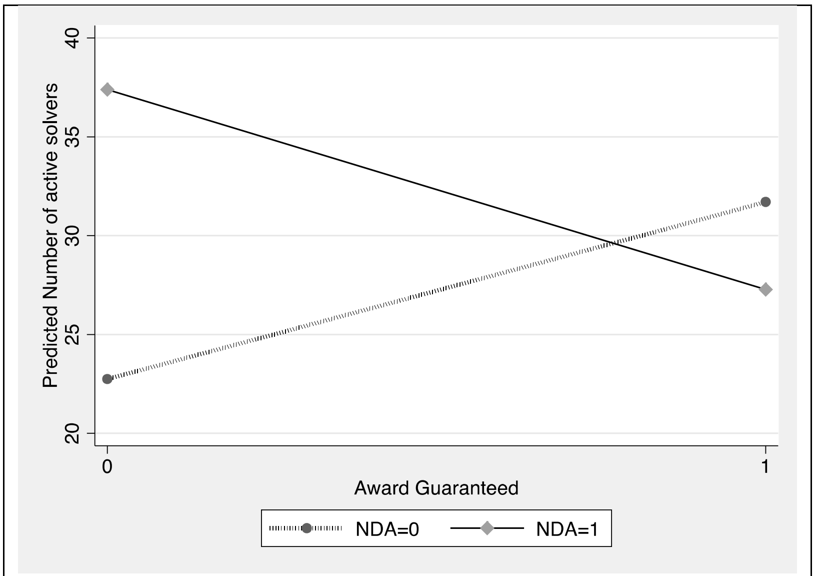

Figure 3(a). Interaction plot of Award guaranteed and NDA on Number of active solvers.

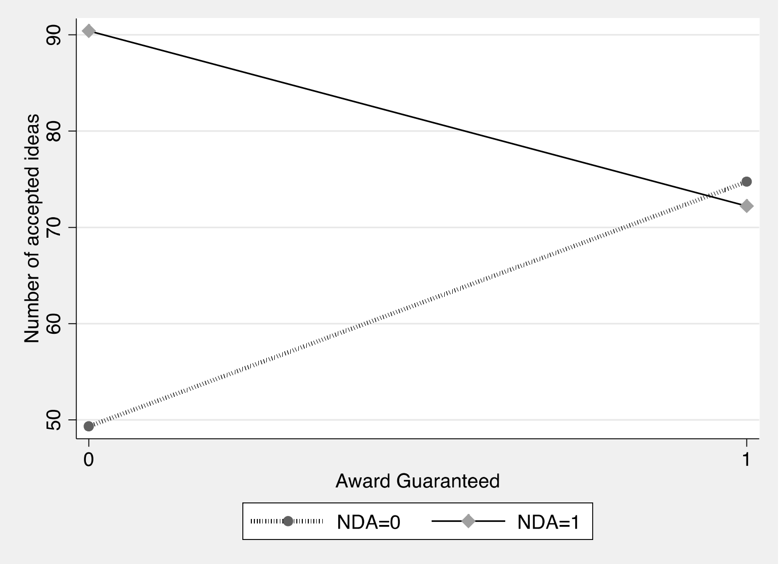

Figure 3(b). Interaction plot of Award guaranteed and NDA on Number of accepted ideas.