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

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'We have over four million people working on Crowdflower syndicated tasks, and I log into our partners sites all the times to make sure that it's a good experience for everyone. There are bound to be some complaints and some issues, but we work as hard as we can to resolve the issues as quickly as possible'

(*Lukas Biewald, Founder and CEO of CrowdFlower*)

Abstract

Crowdsourcing has been considered a new powerful component of innovation. However, scholars are no closer to understanding how organizations (seekers) can design crowdsourcing challenges that are perceived by the external contributors (solvers) as fair. Building on behavioral agency theory, we aim to examine fairness perceptions' effects on the behaviors of solvers that are directed at, and benefit, the success of crowdsourcing challenge. Based on a unique database of 1590 challenges gathered from two online crowdsourcing platforms, we show that solvers will perform well in the crowdsourcing contests if they have ability (knowledge, skills etc.), motivation (i.e., rewards etc.) and fair mechanisms (transparent processes and equity award). Our results indicate that reducing the information asymmetry of solvers engaged in the challenge increases the solvers' perception of procedural and distributive fairness whilst incentivizing their self-selection process. Moreover, posing problems in an 'open' way exposes seekers to possible opportunism risks. Thus, seekers utilize safeguarding contractual mechanisms to mitigate these risks and protect the information shared in a challenge. In turn, designing a challenge with strong policies of risk safeguard worsens the

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benefit that the award guaranteed has in attracting a large pool of participants and a large amount of accepted ideas. Our results not only contribute to crowdsourcing for innovation literature but also to behavioral agency theory.

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 the need for transparency against disclosure to competitors during the 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 can be developed in behavioural agency theory (Pepper and Gore, 2015). Behavioural agency theory is important for understanding the design of fair crowdsourcing tournaments. From an agency perspective, the success of crowdsourcing projects originates from principles (seekers) attracting the most competent and skilled agents (solvers) (Afuah and Tucci, 2012). Thus, whilst classical agency theory places an emphasis on the 'principal', behavioural agency theory focuses on the agent 'solver's' work motivation and performance (Wiseman and Gomez-Mejia, 1998; Pepper and Gore, 2015). Quirky provides a good example of how a company attracts 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 (Jeppesen and Lakhani, 2010). In particular, having a large pool of solvers leads to idea diversity, lessens the effects of solver underinvestment whilst increasing the possibility of receiving, as a minimum, one suitable solution (Terwiesch and Xu, 2008). This argument is 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 for 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 in crowdsourcing mechanisms may be implemented generating unattractive crowdsourcing contests. More recently, Franke et al. (2013) highlight the importance of "fairness" in a crowdsourcing contest; beyond intrinsic and extrinsic motivations, solvers are also concerned about how resources are distributed (*distributive fairness*) and the process of selection (*procedural fairness*). 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 the crowdsourcing context, a theoretical framework does not exist for thinking about how seekers can design crowdsourcing challenges that are perceived by the solvers as fair. Our paper aims 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 crowd contributor works autonomously on their individual solution and the company selects their preferred solution. 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 offers several contributions. First of all, we contribute to crowdsourcing literature integrating the literature on organizational justice (Gilliland 1993; Karriker and Williams, 2007) with the literature on tournament-based crowdsourcing (Afuah and Tucci, 2012; Franke et al., 2013) through the application of behavioural agency theory (Eisenhardt, 1989, Pepper and Gore, 2015). Building on previous studies, we used organizational justice to describe the role fairness plays in 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. It shows a reasonable approach of contracting and resolving agency problems between principal (seeker) and agents (solvers). Furthermore, our model includes a mechanism for the safeguard opportunism risk: it moderates the relationship between fairness perception of solvers and the performance of a crowdsourcing contest. Hence, under the lens of behavioural agency theory, we recognize two main sources of conflict in a typical seeker-solver relationship: lack of fairness and opportunism risk.

Second, past researchers in open innovation (Chesbrough, 2003) and user innovation (Di Gangi and Wasko, 2009) 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 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, research on designing crowdsourcing challenges focusing on the 'seeker' perspective is limited; only one study (Franke et al., 2013) considers fairness in the crowdsourcing context. Franke et al. (2013) examines how the role of the fairness influences 'solvers'' initial decision to take part in a crowdsourcing project; 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 ex ante to participations. They employ a simulation scenario that describes the crowdsourcing tournament's terms and the conditions. 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 examine the influence fairness plays in attracting solvers in an actual scenario by using secondary data. We believe this approach spreads the external validity of our work since we collect data on real behaviours rather than intentions.

We organized the article 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 show the results and outline their theoretical and managerial implications. Lastly, we comment on the study limitations and avenues for future research.

Behavioural agency theory in the crowdsourcing context

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 and work motivation at the center 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, given the available* *opportunities"*. In general, an agency perspective is appropriate to conditions that have a principle (seeker) – agent (solvers) structure. In this study, such a structure is considered in the crowdsourcing context as seekers delegate challenges to solvers to find the best possible solutions. In a typical process of crowdsourcing, the seeker's challenge is broadcast widely to a population of outsiders in form of a challenge (i.e. open call) (Afuah and Tucci 2012;). Prospective contributors evaluate the call and then decide if they want to spend time resolving the problem by developing and submitting solutions and ideas (Howe, 2006; Zhao and Zhu, 2014). The seeker then accepts the solution that most closely matches existing criteria.

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

The first factor is the *lack of fairness*. The lack of proper fairness perception of the crowdsourcing challenge may jeopardise the initiative with the consequence of reducing the number of solvers that is self-selected to solve a problem (Franke et al., 2013). As recognized by the organizational justice scholars, individuals' perception of the fairness affect their behaviours, such as motivation, organizational commitment, performance, intention to remain with the institute (Adams, 1965; Leventhal, 1980; Gilliand, 1993; Cohen-Charash and Spector, 2001; 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 against 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 she/he will not self-select for the tournament (Feller et al., 2012). Thus, the lack of fairness in distributing the incentive to the solver may reduce the efficiency of the crowdsourcing mechanism despite the effort of the seeker to organize it. Furthermore, behavioural agency scholars advise how agents are primarily "loss adverse" than risk adverse (Wiseman and Gomez-Mejia, 1998; Pepper and Gore, 2015); thus, an higher distributive fairness reduces the solvers' perception of bearing some losses in the crowdsourcing contest and therefore increases their willing to participate with effective solutions. Another 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 process conducing to the selection of the winning solution and, since agents are loss adverse (Wiseman and Gomez-Mejia, 1998; Pepper and Gore, 2015), 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 solvers stresses the solvers' 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 increase the agency problem in crowdsourcing contests concerns *opportunism risk*. Agency theory assumes an opportunistic behaviour 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. The seeker could limit the conflict by designing appropriate reward systems for solvers as well as transparent mechanisms. However, this would imply that seeker companies would need to reveal technical and/or confidential intelligence/knowledge about their subsequent development projects (Lüttgens et al., 2014). This exposes seekers to possible opportunistic behaviours by the solvers (Afuah and Tucci, 2013). Such perceived risks bring seekers to design specific crowdsourcing mechanisms able to reduce the likely opportunistic behaviours from external parties. These protection mechanisms have possible drawbacks; in fact, they reduce the transparency of a challenge increasing the information asymmetry of solvers. Thus, risk protection mechanisms defined by the seeker to protect himself from possible intellectual property abuses and confidential threats, might moderate the positive impact that the fairness has in attracting a wide range of potential solvers.

Conceptual framework

In this study, incorporating behavioural agency problems in the crowdsourcing context we argue that the lack of fairness (both distributive and procedural) and the opportunism risk might deteriorate the agency relation between seeker and solvers by affecting the effectiveness and the efficiency of the self-selection process (see Figure 1). We also include in our investigations the underlying question of risk safeguard mechanisms as moderator parameters when designing a crowdsourcing contest.

[Figure 1, about here]

Distributive and Procedural fairness

Fairness was 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 the 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 associated to the apparent fairness of the process of selection (Leventhal, 1980; Gilliand, 1993). Regardless of the outcome, solvers usually desire the crowdsourcing process to be transparent (Di Gangi et al., 2010; Franke et al., 2013). When a crowdsourcing process is perceived to be unfair, the solvers' reactions are predicted to be directed at the seekers, rather than at her/his tasks or the specific outcome in question (Cohen-Charash and Spector, 2001). For example, Di Gangi et al. (2010) show an adverse response to apparent procedural unfairness in a Dell crowdsourcing competition. *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) , which may influence solver's experience and eventually their behaviour leading to poor performance or leaving the project (Cohen-Charash and Spector, 2001).

Unfair procedures can lead to reduced participation, or even to no participation at all, or migration to other crowdsourcing contests (Di Gangi and Wasko, 2009). Having a limited number of participants in a contest may decrease seeker's prospects of discovering a good and relevant solution reducing the overall performance of the challenge (Boudreau et al., 2011).

Which tools do seekers have to influence solvers' fairness perceptions? Solvers looking for contests on a crowdsourcing platform sort many challenges and decide whether to join a specific challenge and submit a solution. This decision is taken considering their loss and risk aversions, and on the based of available information they have on that challenge (Tversky and Kahneman, 1992; Wiseman and Gomez-Meija, 1998; Pepper and Gore, 2015). The seeker who designed the challenge provides this information (Feller et al., 2015). In fact, 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. For example, we reason that an award guaranteed (perception of distributive fairness) should contribute to reducing the "inequity aversion" (Fehr and Schmidt, 1999) perceived by the solver because it signals 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). In fact, if the connection between efforts and skills, which solvers put into solving the challenge, and the expectation of reward is not comparable, then the solvers will become discontented and discouraged from submitting a good solution (Pepper and Gore, 2015). Better understanding what seekers do, feeling assured that they will surely allocate their resources not hiding anything reduce solvers' inequity and losses' perception and it encourages them 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 (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 and, according to behavioural agency theory, the perception of possible losses the solver can bear in a crowdsourcing contest. 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 and the higher their perception 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 influence on its attractiveness and effectiveness.

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

The moderating effect of risk safeguard

In a crowdsourcing contest, since according to agency theory seeker and solvers tend to pursue their own interest, opportunism might cause conflicts between them (Eisenhardt, 1989). The seekers have the possibility to mitigate these conflicts by disclosing information about technical problem and/or revealing sensitive information about their future development projects (Lüttgens et al., 2014). However, posing problems in an 'open' manner exposes seekers to possible opportunistic risks that reduce their ability to capture value from crowdsourcing processes (Feller et al., 2012; Afuah and Tucci, 2013). In fact, 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 her/his market competitiveness (Nambisan, 2002).

In order to mitigate opportunistic behaviours and protect their information, seekers utilize safeguard contractual mechanisms (Nambisan and Sawhney, 2007). 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 (Avenali et al.

2012). By designing these mechanisms 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 by the 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 increase information asymmetry of participants on the execution system and the rewarding schema of a challenge decrease their perceived fairness (both distributive and procedural) and make the solvers less committed. Indeed, even in case the seeker guarantees the award to the winning solver, the presence of undisclosed clauses makes the solver more difficult to verify the transparency of the selection of the winning solution and, therefore, it contributes on a perception of an unequal process and, furthermore it increases the solver's fear of bearing a loss.

In sum, safeguard tools tend to reduce the positive effect that perceived fairness has on challenge performance. Thus, we state the third set of the hypotheses 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 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 we can investigate the participation of the solvers to the challenge (Sun et al., 2014). 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 (crowdsourcing platforms for ideas' competitions) focus on design tasks such as logo, business card and web design. 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 (CrowdSPRING, 2014). 99designs reaches more than '*250,000 graphic designers from 192 countries around the world and hosts more than 370,000 design contests*' (99designs, 2015). Finally, we choose these two intermediate platforms since they are very similar, so we can build a unique dataset putting together CrowdSPRING and 99design's data challenges.

In these platforms, a seeker defines challenges through a problem statement that is openly communicated and publicised, called ''request for proposal'' (RFP). Problems are described by RFPs for solution and also RFPs emphasise the performance standards for a successful solution to meet. Furthermore, the RFP notifies crowds 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 platforms' archives 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 her/his needs. The probability to find 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 concept of "procedural fairness" in terms of *solution sharing*, while the concept of "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 considered 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 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 she/he 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, behavioural agency theory also suggests that individuals consider the distribution of resources between parties (Pepper and Gore, 2015). The sum of money offered by the seeker as a prize, increasing the solvers' outcome, has an effect on equity perception and thus on fairness perception. 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 an official defensible 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 she/he does 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 her/his information from potential solvers' opportunistic behaviours. For these reasons, we choose 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 decide to engage in a confidential relationship recognising the sensitive nature of particular exclusive, confidential intelligence, 0 otherwise.

We consider a number of control variables in the empirical analysis. We control when seeker reveals her/his 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 logarithm of difference between two dates, the deadline and the beginning of a challenge. Since the platforms show different type of challenge, we use four dummy variables (“Logo”, “Website & Application”, “Art, Illustration & Packaging”, “Business & Advertising”) to understand the impact that the *category of challenge* has on the attractiveness and effectiveness. We also control for *advertising*, a binary variable that assumes a value 1 if the challenge is advertised to the web community through newsletters or Twitter or browser pages, 0 otherwise. Sometimes a seeker prefers to address her/his challenge 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 her/his call to a small group of solvers opportunely selected, 0 otherwise. Finally, we control for the effect of the two platforms through a dichotomous variable, *platform*, assuming value 1 when the challenge is broadcasted on 99designs, 0 otherwise (i.e. if the challenge is broadcasted on CrowdSPRING).

Analysis

Model specification

We considered an in depth analysis of the data to select the best fitting method 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 (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. We compare the Poisson predictions for a model equivalent to model 1 in Table 3 for the dependent variable number of accepted ideas. We show Model 4 in Table 3for the dependent variable number of active solvers (model 1: $\chi^2 = 41220.17$, $p = .000$; model 2: $\chi^2 = 117270.8$, $p = .000$). We could conclude that the Poisson distribution is not a good choice due to the large value for chi-square in the *gof* test. 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 output of 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 favour 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.

Findings

Table 1 depicts the descriptive statistics. Table 2 shows correlations' value for all variables. The pairwise correlation matrix does not reveal any criticalities respect to multicollinearity problems.

[Table 1 and Table 2, about here]

Table 3 provides the regression results. 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 H1. 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 H2. 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 negatively moderates the relationship between award guaranteed and number of active solvers.

[Table 3, about here]

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 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, 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 the H3a is not confirmed. Moreover, 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 analysis 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 continuous 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 of 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. Consistent with the results of 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

This study was motivated by important findings in the previous research on tournament-based crowdsourcing. Previous studies found that seekers can benefit from large and fully open contests because they obtain diverse set of solutions, which mitigate and in some cases outweigh the negative effect of solver's underinvestment (Boudreau et al., 2011). The success of a tournament-based crowdsourcing, thus, might depend on the ability of a seeker to drive and influence the self-selection process of the crowd. Moreover, previous literature has recognized that beyond intrinsic and extrinsic motivations solvers have concerns also about fairness (Franke et al., 2013). Thus, in this paper we examined the association between fairness concept, effectiveness and attractiveness of crowdsourcing contest by specifically investigating how seekers can attract a large pool of solvers by designing challenges that are perceived by the solvers as fair. We theoretically grounded this research under the lens of behavioural agency theory (Pepper and Gore, 2015).

Recent research in crowdsourcing fails to find much relevance of both traditional agency theory and behavioural agency theory to explain seeker-solver relationship. This study examined the influence of the behavioural agency theory in crowdsourcing companies and the solvers' relationship with the fairness concept. Extending behavioural agency theory to the crowdsourcing context, we framed hypotheses relating two factors that are sources of conflict within seeker and solver relationship: the lack of fairness and the opportunism risk. Analysing detailed data gathered from 1590 challenges presented on two crowdsourcing platforms, we found three main results. Firstly, we found that both procedural and distributive fairness have a strong impact on the challenge participation and ideas' submission. The challenge attractiveness and effectiveness increase as the perceived procedural and distributive fairness is designed in response to agency problems. Secondly, the risk safeguard mechanism moderates the relationship between the distributive fairness and attractiveness and effectiveness of challenge. Thus, designing a challenge with strong policies of risk safeguard, to reduce the opportunism risk of solvers, worsts the benefit that appropriate reward systems have on challenge performance. Thirdly, no importance is given to risk safeguard mechanism of crowdsourcing when the solvers consider perceived procedural fairness is in place and associated with attractiveness of crowdsourcing.

This study has important implications for research. First, given that the seeker-solver relationship has a principle-agent structure, our results provide support for the application of behavioural agency theory to fairness considerations during the tournament-based crowdsourcing. Nevertheless, the results also indicate that the agency problem in a crowdsourcing context is multidimensional; different aspects of the problems influencing the different fairness components.

The fairness perception of a crowdsourcing contest is considered important for understanding the degree to which the agency problem may exist in a seeker-solver relationship. As concern the perceived sense of fairness in distributing the incentive to the solvers, our findings confirm that mechanisms as the award guaranteed, by signalling to the solver that the seeker is reliable and that she/he will pay out the prize at the end of the contest, enlarge the number of competitors of a challenge and the number of accepted ideas. But this is not enough. In fact, as already recognized by scholars from behavioural agency theory (Wiseman and Gomez-Mejia, 1998; Pepper and Gore, 2015), our findings highlight that solvers are also "inequity adverse" (Fehr and Schmidt, 1999): in fact, the amount of prize was to found have a strong impact on attractiveness and effectiveness of a challenge. Thus, when the solver perceives that the incentive (the amount of prize) is fair compared to the value the solver provides to the seeker, the solver will perceive a sense of justice and she/he will self-select for the tournament (Feller et al., 2012). As concern the perceived sense of fairness in organizing a contest, our findings confirm that clear procedures 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. 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. Since solvers are loss adverse agents (Wiseman and Gomez-Mejia, 1998; Pepper and Gore, 2015), the presence of clear procedures, by reducing the information asymmetry between seeker and solvers, decreases the solvers' perception about possible losses reducing, and increases in this way the efficiency of the self-selection procedure. In sum, in line with behavioural agency theory (Pepper and Gore, 2015) our results indicate that solvers will perform well in the crowdsourcing contests if they have ability (knowledge, skills etc.), motivation (i.e., rewards etc.) and fair mechanisms (transparent process and equity award).

Moreover, the results regarding the risk safeguard mechanism are not straightforward. 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. Thus, as predicted in agency arguments, the protection mechanisms defined by the seeker to protect herself/himself from possible opportunism risks of solvers, reduce the transparency of a challenge increasing the information asymmetry that the solvers have on that challenge. Moreover, we did not find empirically confirmation about the same moderator effect that these 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 an essential component 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 collaborative relations between procedural and distributive fairness, as were documented in the fairness literature (Greenberg 1987; Leventhal, 1990).

Second, our study offers also important contributions to the research on tournament-based crowdsourcing. Contrary from previous studies that basically take a solver's perspective in explaining the challenge performance, in this research we adopt a *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 as in 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 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 enriches external validity of our results.

Lastly, our research has also important 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 promise of a clear, straightforward crowdsourcing process increases the awareness of procedural fairness. This assurance can be attained 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 results on the role of risk safeguard mechanisms in moderating the fairness and challenge performance relation define the crucial role that managers play in designing a contest. 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. This means that managers have to find a trade-off between designing a challenge perceived as fair and designing a challenge in order to protect intellectual property.

Limitations and future research

Our research results and contributions should be appraised whilst taking into account its limitations. Firstly, the analyses are based on secondary data. The major limitation that poses these kinds of data is that the data already exist and so new constructs of interest cannot be added to it. Moreover, secondary data analysis lacks of a confirmatory empirical analysis that can effectively demonstrate that our assumptions about the interpretation of data are appropriate. A second limitation is relevant to the crowdsourcing performance measures we have used. Indeed, a challenge performance should be measured also considering quality aspects of the solution offered by the solvers, such as for example the seeker's satisfaction of the solutions or how the solution fulfils the predefined seeker's challenge criteria. In this paper, to verify our conceptul framework, we adopted two performance measures that evaluate basically the participation of solvers on that challenge and the accepted ideas. Thus, the interpretation of the results can be different in cases where other crowdsourcing performance measures are employed. Lastly, our research focuses on two crowdsourcing platforms for ideas' competitions, CrowdSPRING and 99designs. Although the context is surely appropriate for the issues under investigations, it would be irresponsible to generalize the findings universally to other competitions, such as challenges gathered from crowdsourcing platforms for technologies' competitions (for example Innocentive or NineSigma).

Several opportunities for future research in fairness perception of crowdsourcing emerge. One possibility would be to examine a causal relationship between different kind of fairness (i.e., procedural fairness and distributive fairness). For instance, Leventhal (1980) proposed that perceived 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 fairness aspects in crowdsourcing context would be explored in future research via paying thoughtful consideration to issues of fairness source, and their interactions not only from solver's perspective but also from seeker's perspective. Behavioural agency theorists have started considering the importance of the agent's work motivation, including intrinsic and extrinsic motivations in the principle and agent relationship (Pepper and Gore, 2015). Specifically, future research in crowdsourcing should benefit from including the relationship between motivation of solvers and perception of their fairness of the system, when the fairness and efficiency and attractiveness of the crowdsourcing construct are applied, so that each of the fairness elements has a principal equivalent. Once these measurements are considered, further attention to new mediators and moderators of fairness and success of crowdsourcing should be explored.

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

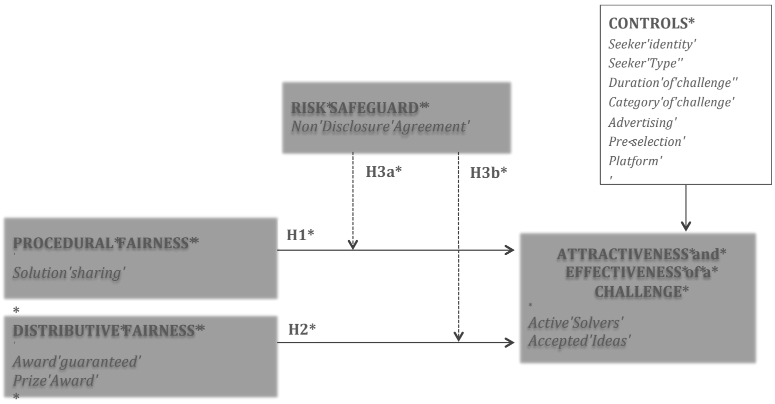

Figure 1. Conceptual Model.

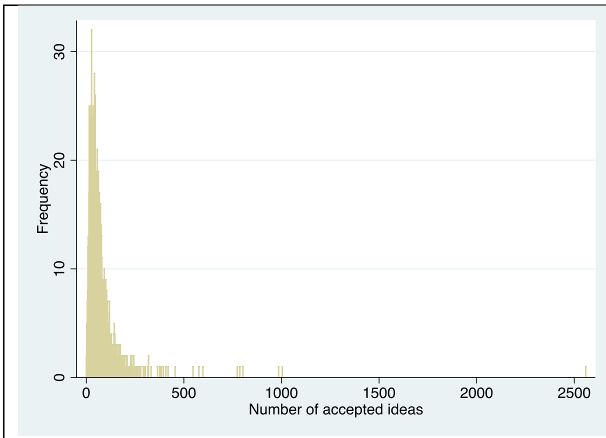

Figure 2(a). Number of accepted ideas variable distribution.

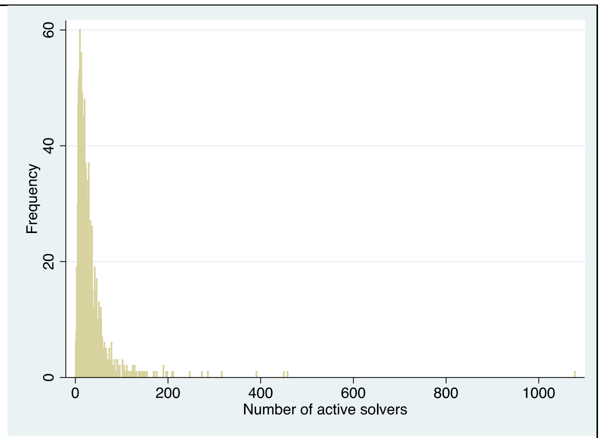

Figure 2(b). Number of active solvers variable distrubution.

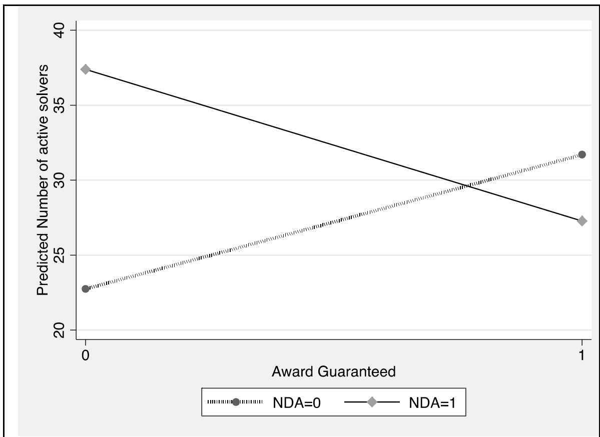

Figure 3(a). Interaction plot of Award guaranteed and NDA on Number of active solvers.

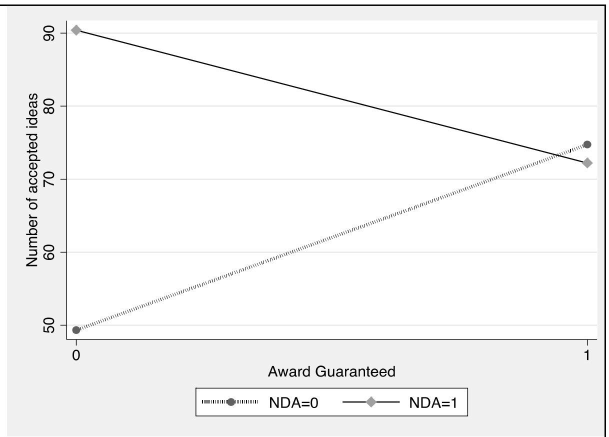

Figure 3(b). Interaction plot of Award guaranteed and NDA on Number of accepted ideas.