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Invited Review

Crowdsourcing contests

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A R T I C L E I N F O

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A B S T R A C T

In a crowdsourcing contest a requester posts a task (e.g. logo design, programming task) on a platform and announces a monetary reward that he is willing to pay for a winning solution. Contestants (e.g. designers or programmers) submit solutions on the platform and the requester chooses the best solution (possibly more than one) and awards the prize. On-line platforms for crowdsourcing contests are already abundant and growing rapidly in market size. In this survey we present two streams of literature that study crowdsourcing contests. The first is theoretical research, which tries to capture the characteristics of these contests, describe them as a game and then analyze the equilibrium behavior of contestants. The second is the empirical research which collects crowdsourcing data and analyzes the behavior of the contestants in these platforms. The aim of this survey is to clarify the current status of the research of incentives and behavior of contestants, organizers and the platform in crowdsourcing contests and to highlight the many questions that are still open.

1. Introduction

The word crowdsourcing has been used to describe several different activities. In all of these activities there is an appeal to the crowd in different ways, mainly through internet platforms and for many different reasons. This paper reviews both empirical and theoretical research on crowdsourcing contests in which tasks are presented to the crowd and a contest is held to determine the best solution to each task. Each task (e.g. translation, logo design, software development) is described in words, offers a monetary reward for the best solution (or sometimes for more than one solution) chosen by the organizer of the contest, and has a deadline attached to it. In recent years platforms for such contests have grown rapidly. Millions of people around the world engage in competing for these tasks' rewards and millions of dollars are transferred from the task organizers to the solvers. It is interesting to note that many of the crowdsourcing platforms are used for design contests (e.g. logo designs, package designs). The design market is increasingly turning to crowdsourcing as a source of labor, earlier and faster than other markets.[2] Hand in hand with the growth in crowdsourcing activity the literature on crowdsourcing contests is also expanding. Researchers from fields such as operations research, computer science, management, artificial intelligence, economics, and information systems study the structure of these platforms and the behavior of the contestants in these contests. Unlike previous reviews (e.g. Mao, Capra, Harman, & Jia, 2017; Yuen, King, & Leung, 2011; Zhao & Zhu, 2014) which aimed to characterize crowdsourcing and to identify the projects for which it is best suited, this review focuses on the incentives and the behavior of the participants in online crowdsourcing contests.[3]

There are many different platforms for crowdsourcing contests and many parameters that can affect the behavior of the contestants. In some of the platforms the contests are open and the submissions can be viewed by all (e.g. "99designs", "Crowdspring"), while in other platforms only the organizer can view the submissions (e.g. "TopCoder"). Some platforms leave it for the organizer to decide if she wants an open or closed contest and some give contestants the choice as to whether to submit openly or blindly - using a password such that only the organizer can see the specific submission. Some platforms hold multi-round contests

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[1] This work was done in part while the author was visiting the Simons Institute for the Theory of Computing, Berkeley, CA, USA

[2] Aannual crowsourcing report by eYeka: https://en.eyeka.com/resources/reports

[3] It is important to note that following our definition above of a crowdsourcing contest we will not cover in this paper the literature that focuses on platforms in which the participants in a task receive reviews from the community and the winner(s) is determined according to these reviews (e.g. "Threadless.com"). We will also not review papers on types of crowdsourcing websites in which the crowd is called to contribute to a given task and everyone receives some payment. Therefore we will not cover activities on websites such as Amazon's Mechanical Turk or "freelancer.com".

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and/or include a registration phase before the contest, while others only hold one round. In some platforms the organizer may choose any amount of money as a prize while in others she must choose one of a predetermined set of possible prizes. In some cases, if the organizer decides she is not satisfied with any of the submissions, she can choose not to award a prize at all, while in others the organizer has to choose a winner and award a prize even if she is unhappy with the submissions (payment is guaranteed to a winner). There are platforms that allow contestants more than one submission to the same contest while others do not allow that.

Another category of features relates to the communication between contestants and between contestants and organizers. Some platforms offer a feedback system where the contestants can obtain feedback from the organizer and then resubmit a solution. Almost all platforms use some kind of reputation system. Contestants can then accrue reputation, observable to all other contestants, although the specific computation of the reputation of a contestant differs from one platform to another. In some platforms it is based on how many contests the contestant has won, in others it is based on the amount of money that she has accrued and in yet others it is based on the organizers' feedback regarding her submissions.

However, the main features of the environment are common to all crowdsourcing platforms - a contestant enters the site, chooses a task or a contest among a large set of open tasks or contests and invests effort in an attempt to win the specified reward (or one of a set of rewards). The aim of this review is to shed light on what motivates and may affect the behavior of the participants on these platforms.

We review here both theoretical and empirical papers on crowdsourcing contests. The review of the empirical research examines the factors that affect the behavior of contestants, in particular their willingness to participate in a contest and their level of performance using data from a wide range of crowdsourcing websites including: TopCoder, Taskcn, 99Designs, Crowdspring, DesignCrowd, Innocentive, Kaggle.com, Lancers.jp, zhubajie.com, Logomyway.com, witmart.com, www.680.com, and Atizo.com. These papers shed light on important factors that turn a crowdsourcing contest into a successful one and by that may contribute to the design of better and more efficient platforms for crowdsourcing contests.

The theoretical research we review here mostly uses game theoretic and mechanism design tools to describe a contest as a game between the contestants (and sometimes also the organizer). There is a large body of theoretical literature on contest theory within game theory. This literature has been surveyed in the past e.g. in the books by Konrad (2009) and Vojnovic (2015) and in Corchón (2007). In brief, the fundamental questions addressed by this literature are the existence and uniqueness of the equilibrium in different contest formats (e.g. Hillman & Riley, 1989; Hillman & Samet, 1987; Nitzan, 1994), the optimal number of prizes in contests (Moldovanu & Sela, 2001; Sisak, 2009) and the effects of constraints such as effort caps (Che & Gale, 1998). In these studies, a contest is analyzed as an isolated event in which contestants invest efforts with irreversible costs that determine the quality of their submission. The winner is then selected according to a predetermined contest success function.

However, crowdsourcing contests do not meet the classical theoretical assumptions in the contest theory literature for many reasons. First, in a crowdsourcing platform contests are not isolated events. When a contestant chooses to participate in a particular crowdsourcing contest, she has already chosen among a variety of ongoing contests. In many cases, she can then decide to submit more than one solution. In most platforms she also receives feedback from the organizer and may then improve her submission or learn from other contestants' feedback what is the desired solution. In crowdsourcing contests, the classic assumption that a quality of a submission is a function (deterministic or noisy) of the contestant's effort (and sometimes also her ability), may also be violated. In turn it may be the case that creativity and innovation have a larger impact on the outcome of a submission than the effort. In this case it might be more suitable to describe a contest as a search process in which contestants may conduct costly experiments/research and at each period, with some probability (that may depend on the research effort), success occurs. In a search model the quality of the outcome is not uncertain. It is the timing and sometimes the feasibility of success that is uncertain.

Crowdsourcing contests are also characterized by both a large and uncertain number of participants and a large degree of noise in the determination of the winner. Since there are usually no objective measures by which the solutions are assessed, different organizers may award the prize to different contestants even if all the submissions are identical. In recent years researchers have developed novel theoretical models that capture some of these differences and we review them here. We review papers that take a different approach to studying contests from the vast existing literature on contests - that is, an approach that mirrors some aspects in the reality of crowdsourcing contests. The aim of this part of the literature review is both to characterize the results that were already obtained and to highlight the gaps between models and reality that still exist.

2. Theoretical research

This section is organized according to the theoretical approaches that characterize the different studies. Some studies characterize an equilibrium of a game and then analyze how changing some parameters of the game (e.g. the number of prizes, the size of the prize, the entrance costs and so on) will change the behavior of the contestant in a desired way. These papers analyze a single contest and are surveyed in Section 2.1. A different approach is presented in Section 2.2 in which the emphasis is on innovation and creativity. The papers presented in Section 2.1 assume that a quality of a submission is a function (deterministic or noisy) of the effort and ability of the contestant. The quality is then observed by the organizer of the contest who awards the prize to the best quality submission (or possibly to more than one submission). In Section 2.2 the focus shifts to the effect of the competitive environment on the creativity and innovation of the contestants, measured as the amount of experimentation the contestants undertake. It is assumed that a success (i.e., high quality submission) occurs with some probability whenever the contestants experiment and the more they do the probability of success increases. The papers surveyed in this subsection therefore study how the characteristics of the contest increase the experimentation aspect of submissions.

Section 2.3 surveys papers that study the question of how an individual chooses among many contests. In these papers there are multiple contests going on simultaneously and the participants choose among them. The goal is to understand how they choose. Section 2.4 surveys papers in which the platform of the contests is also a player in the game and examine how can it improves its profits. Sections 2.3, and 2.4 are much shorter than Sections 2.1 and 2.2 as these aspects of crowdsourcing are yet very much unexplored. We will elaborate on this point in the last section (Section 4) where we discuss the main open problems of crowdsourcing contests.

2.1. Optimal contest

The aim of modeling a contest as a game is to characterize contestants' equilibrium behavior given the rules of the contest and then explore how changing these rules affect the players' behavior and as a consequence the contest's performance. The parameters that appear in most of these studies include the number of prizes and their sizes, the possibility of exclusion of participants, and entrance cost. By changing them the organizer can improve the contest's performance in the direction of designing an optimal contest. The performance of a contest is defined differently in each paper. The common assumption is that the quality of a submission is a function (deterministic or noisy) of the contestant's ability and effort and that once all submissions are made their qualities are observed by the organizer of the contest who awards the prize to the best quality submission (or sometimes more than one prize such that the second highest prize is awarded to the second highest quality submission and so on). The organizer's utility is some function of these qualities. She may enjoy only the quality of the best submission or a function of the qualities of all or of some of the submissions.

2.1.1. Output is a deterministic function of effort

Most of the classic literature on contests (e.g. Hillman & Samet, 1987; Moldovanu & Sela, 2001) assumes that the quality of a submission is a deterministic function of two variables - the contestant's skill, or ability, which is sometimes assumed to be her own private information, and the contestant's effort. Therefore, when an equilibrium is identified given the contest's parameters it is then straightforward to examine what happens to the quality of the winning submission (or some other function of the qualities of the submissions that the organizer wishes to maximize) in equilibrium when these parameters are changed. We review here studies of crowdsourcing contests that keep the assumption of the deterministic connection between effort and quality and enhance our understanding of the design of an optimal contest in situations that approximate crowdsourcing contests.

Archak and Sundararajan (2009) study a symmetric contest with N contestants and L prizes, $M_1 \geq \cdots \geq M_L$. The contestants' ability is drawn from a continuous distribution on a bounded support and is private information of the contestants. The cost of effort of a contestant of ability $\theta \in \left[\underline{\theta}, \overline{\theta}\right]$ who invests an effort (bid) of e is given by $C(\theta, e) = \theta e$.[4] The contestants may be risk neutral or risk averse but all have the same risk attitude. A contestant therefore aims to maximize

$$\sum_{i=1}^{L} p_i(e) V(M_i) - \theta e$$

where $V(M_i)$ is the contestant's utility from prize i of size M_i and $p_i(e)$ is the probability that she wins prize i when she invests an effort e, given some fixed behavior of her opponents. The contest success function is an all-pay function where the largest prize is awarded to the highest quality submission (in this paper the quality is equal to the contestant's effort), the second largest prize is awarded to the second highest quality submission and so on. The authors start by proving that for a given set of prizes the contest has a unique, symmetric pure-strategy Bayesian equilibrium where the equilibrium bid function $b^*(\theta)$ is strictly decreasing in θ. This is a well-known result for the all-pay auction which they extend to the risk averse case. They also show that in this equilibrium contestants with greater ability (lower θ) receive a higher expected surplus. In crowdsourcing contests the number of participants is often very large. While classical contests literature assumes a finite number of participants (and sometimes only two), here the authors derive asymptotic results for the case where the number of players N goes to infinity. They use their asymptotic results to derive the optimal prize structure (optimal number of prizes and their sizes) for a budget-constrained organizer who wishes to maximize a weighted sum of the quality of the top K submissions, each by a given weight μ_k. When contestants are risk-neutral, the optimal design of the crowdsourcing contest with a fixed budget involves allocating all of the budget to the top prize but this may change when contestants are sufficiently risk averse and may involve offering more prizes than the number of desired submissions (K).

Ghosh and Hummel (2012) consider a contest with n contestants where the quality (q_i) of a submission is a function of both the effort of the contestant (e_i) and her ability (a_i) which is her private information. The abilities a_i are i.i.d and are drawn from a distribution with CDF $F(\cdot)$ on [0, 1]. The organizer's objective is to maximize some function of the number of submissions and their qualities: $V\left(m, q^1, \ldots, q^m\right)$ where q^i denotes the quality of the ith best submission. This modeling choice allows for many different optimization goals as may be the case with different organizers on crowdsourcing contests platforms. They first assume that the quality of a submission depends only on the expertise of the contestant, i.e., $q_i = a_i$, which represents a case in which contestants differ in the extent to which they are able to answer a question but it would take all individuals similar levels of effort to actually contribute their knowledge. This type of contests were not studied in the classic contest theory literature where it is always assumed that effort affects a contestant's probability of winning (indeed the definition of a contest in the classic literature is a game in which contestants exert costly efforts in an attempt to win a prize). For this case the authors show that a two-rewards mechanism (one reward for the winner and a smaller reward for all other participants, possibly zero) can always implement the designer's objective in the Bayes-Nash equilibrium of the game. Moreover, they show that for any two rewards, $p_B > 0$ for the winner and $0 \leq p_C < p_B$ for all others, there is a threshold $a^*(p_B, p_C)$ such that in equilibrium, each contestant i exerts a positive effort (i.e., participate in the contest) if and only if her ability $a_i \geq a^*(p_B, p_C)$. The unique equilibrium threshold $a^*(p_B, p_C)$ varies continuously with p_B and p_C. Finally they show that if the threshold that the organizer would like to implement in equilibrium is independent of n, the rewards as a function of n, $p_B(n)$ and $p_C(n)$ are strictly increasing in n. In the endogenous effort case where the quality of the submissions depends on both the efforts and the abilities of the contestants in a non degenerate way and the cost of effort is given by $c(e)$, there also exists an equilibrium in which all contestants use a symmetric threshold participation strategy (a contestant participates if and only if her ability is greater than a common threshold) and conditional on participating, each contestant chooses an effort level using a symmetric strategy that is a function of her ability a_i. In this case, however, for any two-rewards mechanism there is no equilibrium in which contestants follow strategies that maximize the designer's utility V. Consequently, the designer will not be able to implement her optimal utility using two rewards. However, if the cost of effort for a contestant does not grow too rapidly (with the effort) then by adding a random noise to $q_i(a_i, e_i)$, the organizer can choose the values of p_B and p_C such that it is an equilibrium for contestants to follow strategies that maximize the mechanism designer's goal.

In Ghosh and Kleinberg (2014) restrict their attention to the case where the quality of the submission depends only on the contestant's ability (the first case described above). They show that the optimal prize structure that maximizes any increasing function of the quality of the submissions is such that each of the top j^* quality submissions receives the same prize V/j^*. Where j^* depends on the homogeneous cost of effort c and the distribution from which the abilities are drawn. They then analyze a contest in which players differ not only in their ability but in their cost of effort as well. Their main result is that the winner-takes-all

[4] Note that a higher type (θ) is associated with a higher cost and therefore a less able contestant.

contest (i.e., a contest with a single prize) is a 3-approximation[5] of the optimal contest when the principal's objective is to maximize the quality of the best submission.

Gao, Bachrach, Key, and Graepel (2012) consider the trade-off between the expectation of the quality of the winning submission and its variance in an all-pay contest. Since the quality of the winning submission is a random variable the organizer of the contest in their paper seeks to maximize (by changing the number of participants) the expectation of the quality of the winning submission while reducing its variance (i.e., the risk). This approach is mostly suitable to contest in which a solution is required to a problem (e.g. coding contests or data analysis contests) and then it is highly desirable to increase the expected value of the best solution while reducing its variance. They assume that the quality of a submission is equal to the effort that the contestant exerts. They consider first the symmetric mixed strategy equilibrium of a complete-information all-pay contest (with a single prize that is awarded to the highest effort) and show that a contest with only two players maximizes the expectation of the highest effort while simultaneously minimizing its variance (over all other number of participants). They then analyze other, more complex contests in which the contestants are divided into equally sized groups each competing in a different contest and the reward is divided between the contests. They again show that dividing the contestants into groups of two contestants results in the highest expectation of the highest effort (among all contestants) as well as the lowest variance. Moreover, they empirically test their theoretical findings on data gathered from Amazon Mechanical Turk. They show that the 2-pair contest achieves the highest expected utility for the principal of all the designs tested, as well as the lowest variance.

Korpeoğlu and Cho (2018) examine a contest in which a submission quality is a function of the players' productivity, ability and effort. In other words, contestant i's submission quality is given by

$$v_i(\beta_i, a_i, e_i) = \beta_i + r(a_i, e_i)$$

where β_i is the expertise level of contestant i, a_i her productivity level and e_i her effort. Her cost per unit of effort is c_i. Based on the quality vector $(v_1, \dots v_n)$, the organizer's payoff is determined as a weighted combination of the quality of the best submission $\max_i v_i$ and the average quality of all submissions $\frac{1}{n}\sum_{i=1}^{n} v_i$. The organizer announces prizes $A_1, \dots A_n$ to be awarded to the best quality submission, second best quality and so on. They demonstrate the generality of their formalization by showing that many types of contests that had been studied in the literature are special cases of theirs. When $a_i = 1, \beta_i = 0$ and $r(e_i) = \theta e_i$ for all i and players are heterogeneous in c_i, the contest is called "cost-based" project and is in fact the all-pay contest that is analyzed in Moldovanu and Sela (2006). When $a_i = 1, c_i = c$ and $r(e_i) = \theta \log e_i$ for all i the contest is "expertise-based" and is analyzed in Terwiesch and Xu (2008) and when $\beta_i = 0, c_i = c$ it is a "productivity-based" contest in which players are heterogeneous in their productivity level a_i and is similar to the contest studied by Ghosh and Hummel (2012). In this case β_i is similar to the ability of the contestant in Ghosh and Hummel (2012) and in Korpeoğlu and Cho (2018) it is assumed, moreover, that ability and effort have an additive effect on quality. They show that in equilibrium contestants with high expertise (β_i) would raise their effort when more contestants enter an expertise-based project (i.e., when n increases), in contrast to previous results. Moreover, they show that in the equilibrium of an expertise-based project only participants with an ability higher than some threshold will participate (exert a positive effort).

Jian, Li, and Liu (2014) analyze the question of open contests vs. blind ones. They use theoretical results from the contest literature to compute the expected highest effort (or quality of the best solution) in a simultaneous incomplete-information all-pay contest vs. in a sequential one in which players decide on how much effort to exert sequentially having observed the decision of previous players (Ludwig, 2006; Morgan, 2003; Segev & Sela, 2014). This question is extremely important to the design of crowdsourcing contests platforms. As mentioned above platforms differ in this feature and some conduct open contests while other closed contests. They show analytically that with ex-ante symmetric players, simultaneous contests produce higher-quality best solutions than sequential contests. They then conduct a laboratory experiment to test this theoretical prediction as well as the prediction that simultaneous contests are more efficient than sequential contests. Their data supports both predictions. It is therefore puzzling that many of the crowdsourcing platforms conduct open contests in which players observe their opponents' submissions. However, the theoretical comparison between the two settings (simultaneous vs. sequential) makes many assumptions that do not hold in reality. Among these assumptions are the symmetry of the contestants (their types, or abilities, are drawn from the same distribution), and the assumption that the number of contestants and their order in the sequential contest are exogenously determined and are known to all. Many platforms allow the organizers to give feedback to contestants and then others may learn from it. This aspect is also missing from this current comparison. Finally, the effect on creativity and innovation that open submissions may have as in Gross (2018) is also excluded from the model of Jian et al. (2014).

2.1.2. Output is a stochastic function of effort

A more recent approach to the study of contests, and one that seems to be better suited to the crowdsourcing contests world, assumes that the quality of a submission is stochastically connected to the effort of the contestants (and ability may have a deterministic or a stochastic effect on quality). In the contest theory literature a contest success function suggested by Tullock (1980) is the most common stochastic formulation of the connection between effort and probability of winning. According to this contest success function if contestant i exerts an effort e_i then her probability of winning the contest is $\frac{e_i^r}{\sum_{j=1}^{n} e_j^r}$. The assumption is that quality is not fully observed by the organizer and therefore given the vector of efforts of contestants, winning is only probabilistic in the efforts. The parameter r is usually referred to as the contest precision. A higher value of r implies a higher probability for the highest effort to win but no finite r results in the highest effort winning with certainty. When r goes to infinity this function converges to the all pay contest success function where the prize goes to the contestant who exerts the highest effort.[6] The papers we review below take a different approach to the stochastic nature of the contest. in these papers it is assumed that the quality of a submission is determined by the effort but with some noise. Therefore a contestant's effort translates into quality stochastically but then, given the qualities, the submission with the highest quality wins. This describes the stochastic nature of the evaluation of the submissions by the organizer. The way the organizer determines the quality of a submission is stochastically dependent on the effort (this reflects organizers' different tastes for example) but once quality is determined the organizer does not choose the winning submission randomly.

[5] This statement means that the ratio between the expected payoff of the principle in the optimal contest to her payoff in the equilibrium of the contest with a single prize is at most three.

[6] See Clark and Riis (1998) for a characterization of pure strategy equilibria, Ewerhart (2015) for a characterization of mixed strategy equilibria and Gallice (2017) for an approximate solution concept.

Xu and Larson (2014) study an all-pay contest in which the organizer is interested in the quality of the best submission. If a contestant of expertise (type) θ_i invests an effort of e_i then the quality of her submission is given by

$$q_i = \theta_i e_i + \varepsilon_i$$

where ε_i are i.i.d., with a cumulative density function F. The authors examine the possibility of excluding some of the contestants. They consider an incentive-compatible direct mechanism ("Top-K") in which contestants announce their types (expertise) and how much effort they are willing to exert and then the mechanism chooses the K contestants who announced the top K qualities without the noise term, $\theta_i e_i$ to participate in the contest. The mechanism then determines the entry fee that they would pay. The selected contestants participate in the contest and the winner (highest quality after the random shock is realized) is awarded the prize M. Xu and Larson characterize the conditions under which this is a truthful mechanism (i.e., contestants will announce their true type) and show how to compute a lower bound on the difference between the social welfare from the "Top-K" mechanism and the social welfare when all contestants participate. Finally they find the lower bound on the size of the reward such that the conditions that ensure truthfulness hold.

Ghosh and Hummel (2015) consider a setting in which the quality of a submission is the sum of the effort and a random variable, that is: $q_i = e_i + \varepsilon_i$ where the ε_i are i.i.d. across contestants. They then consider rank order mechanisms that assign a reward A_j to the contestant with the j-th highest quality and assume throughout that $A_1 \geq A_2 \geq \cdots \geq A_n \geq 0$. They also consider mixed cardinal-ordinal modifications of a rank-order mechanism, of the form $M(g_1(q_1)A_1, \ldots, g_n(q_n)A_n)$, which awards the contestant with the j-th ranked submission of quality q_j a prize $P_j = g_j\big(q_j\big)A_j$, where $g_j(q)$ is a non-decreasing function of q satisfying $0 \leq g_j(q) \leq 1$ and represents the fraction of the prize A_j that a contestant obtains for achieving rank j if she produces a contribution with absolute quality q. When $g_j(q) = 1$ for all j and all q this mechanism reduces to a rank order mechanism. The principal's objective is to maximize some utility function $W(q_1, \ldots, q_n)$ of contestants' submissions qualities in equilibrium. Their main result shows that the functions $g_j(q)$ that optimally modify the rank-order mechanism using cardinal information are step functions that increase from 0 to 1 at some threshold score. In other words a contestant that is ranked j will receive prize $A_j$only if the quality of her submission is above some threshold. Moreover, if the noise density f is single-peaked at 0, then the optimal threshold mechanism applies the same threshold to each rank j and this threshold decreases with the number of contestants. Finally, the authors use simulations to demonstrate the advantage of using cardinal quality information in addition to relative information about quality in terms of maximizing the organizer's objective.

Stouras (2017) adopts the same model as Ghosh and Hummel (2015) and adds the ability of contestants. He assumes that the quality of a submission is given by

$$q_i = e_i(a_i) + \varepsilon_i$$

where $e_i(a_i)$ is the effort of a contestant with ability a_i and ε_i is a realization of a random variable. The ability a_i is contestant i's private information and is drawn from a cumulative distribution function F. The noise terms are drawn i.i.d. from a cumulative distribution function G. A contestant's cost of effort is given by $c(e_i)$. The organizer offers a single prize to the highest quality submission. Stouras shows that in the unique Bayes-Nash equilibrium of the game (uniqueness is guaranteed under mild restrictions) there exists a lowest ability $a_{\min}$ such that a contestant exerts a positive effort in equilibrium if and only if her ability is higher than $a_{\min}$.

In Stouras, Hutchison-Krupat, and Chao (2017) the authors generalize this model and introduce an entry fee. The contestants make two decisions simultaneously - they decide whether to participate and how much effort to exert. The contestants cost of effort is linear $c(e_i; a_i) = \frac{e_i}{a_i}$. The quality of a submission is given by

$$q_i = \gamma a_i + (1-\gamma)e_i + \varepsilon_i$$

where as before ε_i is a random shock. The parameter $\gamma \in [0, 1]$ represents the specifications of the contest - as γ increases the ability of the contestant plays a more substantial role in the resulting outcome of her submission. The organizer of the contest offers m identical rewards to the best m submissions. The organizer aims to maximize the expected quality of the highest quality submission. The authors characterize the unique symmetric pure strategy equilibrium of the game and find the number of participating contestants (out of a population of N) for each number of awards (m). The authors provide conditions that guarantee with certainty that the full population of potential solvers enter the contest, and conditions when no one chooses to enter. Moreover, they characterize a mixed strategy equilibrium in which each contestant randomizes on her entry decision. They show that the expected number of participants is maximized at a unique number of prizes m_0. For small enough γ they find the equilibrium effort exerted by a contestant with ability $a_i \geq a_{\min}$. Their main result is that a unique prize maximizes the expected quality of the highest quality submission.

In Terwiesch and Xu (2008) each contestant is endowed with an expertise level and can exert effort. Moreover, a contestant can conduct trials (experiments) before she submits the solution and the best trial will contribute to the quality of her submission. The quality of a submission is thus the sum of the expertise (β_i), the value of the improvement effort ($r(e_i)$) and a random variable which is the maximum of a set of independent experiments (random variables):

$$v_i\big(\beta_i, e_i, m_i, \xi_{i1}, \ldots, \xi_{im_i}\big) = \max_j \big\{v_{ij} = \beta_i + r(e_i) + \xi_{ij},\ j = 1, 2, \ldots, m_i\big\}.$$

A contestant pays the cost of her improvement effort - $c_1 e_i$ and a cost for each experiment she conducts - c_2 (the parameters c_1 and c_2 are the same for all contestants). The authors define three types of projects. An *ideation* project is a project in which the expertise is the same across all players and the number of experiments is fixed at 1 for all players ($\beta_i = \beta,\ m_i = 1$). In an ideation project, the quality of a solution has a significant noise term that reflects the heterogeneity by which organizers evaluate the solvers' solutions. A *trial-and-error* project is a project in which the expertise is the same across players and the players can only invest in experiments but not in an improvement effort ($\beta_i = \beta,\ e_i = 0$). In this case the solver exerts effort by experimenting, and there is no way of obtaining a deterministic return to effort. Finally, an *expertise-based* project is a project in which there is no stochastic influence of the random noise and thus experimentation is not necessary ($\xi_{ij} = 0$). Quality is driven by expertise and improvement effort only. In all these projects, the organizer's payoff is a weighted combination of the quality of the best solution and the expected average quality of all solutions. When the number of possible prizes is at most two (the highest prize goes to the highest quality submission and the second highest to the second highest quality submission) it is shown that a single prize is optimal for the organizer in ideation and trial-and-error projects but may not be optimal for expertise-based projects. The authors characterize the equilibrium behavior (e_i, m_i) of the contestants and the expected number of participating contestants for each type of project. Finally they show that if the organizer can charge an entry fee to a participating contestant and if, in addition, her objective is to maximize the quality of the best solution only, then for ideation projects and trial-and-error projects, the optimal entry fee is zero.

Ales, Cho, and Korpeoğlu (2017) generalize Terwiesch and Xu (2008) to allow for noise that is independent of the trials of the contestant. They study the optimal allocation of prizes. In their model the quality of a contestant's submission is given by

$$v_i\left(e_i, m_i, \xi_{i1}, \ldots, \xi_{im_i}\right) = r(e_i) + \max\left\{\xi_{ij}, j = 1, \ldots, m_i\right\} + \tilde{\varepsilon}_i$$

In other words each contestant decides how much effort to invest in a deterministic improvement and how many trials to conduct before submitting a solution (as in Terwiesch & Xu, 2008), but in addition, the quality of the contestant's submission depends on a style shock $\tilde{\varepsilon}_i$ which is unknown to the contestant before she submits her solution. The organizer of the contest chooses the reward scheme that will maximize the expected quality of the sum of the K highest-quality submissions (she benefits from the K best solutions) minus the sum of the rewards. The authors first find the conditions (necessary and sufficient) under which granting a single prize is optimal for the organizer. These conditions ensure that a marginal increase in a contestant's effort increases her probability of becoming the winner more than it increases her probability of attaining any other rank. When the conditions are violated granting a single prize is no longer optimal. It is further shown that if it is optimal to award a single prize, then the size of this optimal prize increases with the number of valuable submissions, K while it may be increasing, constant, or decreasing with the number of participants N.

In Korpeoğlu, Korpeoğlu, and Tunc (2018b) the authors add a time dimension to the contest description. Indeed, in most of the crowdsourcing platforms, organizers may choose the duration of their contest. Each contest is characterized by a contest duration T and the cost of a contestant is a function of the effort she exerts throughout the contest duration. The quality of a submission is given by $y_i = r(e_i) + \tilde{\varepsilon}_i$ and the cost of effort is $\psi(e_i, T) = ce_i^b T^{1-b}$ for $c > 0$. The organizer of the contest is interested in the quality of the sum of the best K solutions discounted over the time duration, and sets the optimal time duration as well as the optimal prizes. They show that the optimal contest duration T increases with the contestants' output uncertainty (the shocks $\tilde{\varepsilon}_i$) and decreases with the marginal impact of the contestant's effort on the quality of her solution. They conclude that the optimal contest duration may increase with the novelty and the sophistication of solutions that the organizer seeks.

Cavallo and Jain (2012) assume a more general stochastic relation between the efforts of the contestants and the quality of their submissions. In their model, each contestant $i \in I$ has a skill level $s_i \in [0, 1]$. The cumulative distribution function of the quality of submission (output) $F^{\nu}_{s_i,\delta_i}$ depends on the effort level of the contestant, δ_i, her skill, s_i, and ν, the private type (value) of the organizer. This distribution is increasing (in terms of first-order stochastic dominance) in both the skill level and the effort. The organizer seeks to maximize the expectation of the highest quality submission minus the total effort expended:

$$E\left[\max_{i \in I} Q_i(\nu, s_i, \delta_i)\right] - \sum_{i \in I} \delta_i \tag{1}$$

where $Q_i(\nu, s_i, \delta_i)$ is the random variable, for which the cumulative distribution function is $F^{\nu}_{s_i,\delta_i}$. An efficient policy $\delta^*(\nu, s)$ is a vector of effort levels that maximizes (1) given values of ν and $s = \left(s_1, \ldots s_{|I|}\right)$. The authors first derive conditions on the distributions such that a best response of a contestant is an extreme value of effort (either the lowest or the highest possible). Then, under these conditions, an efficient effort policy consists of full-effort participation by a subset of the contestants and no participation by the others. When all contestants have the same skill (i.e., $s_i = s_j = s$ for all contestants), the authors compute the number of active contestants (m^*) in the efficient policy under the assumption that the conditions for an optimal extreme-effort policy hold and therefore each active contestant exerts the highest possible effort. When skill is not the same across contestants, the authors determine a precise optimal policy by iteratively considering each contestant, in decreasing order of skill, accepting contestants for (full-effort) participation until the objective of the organizer is no longer improved by including the next contestant in the list. They show that an extreme-effort policy is optimal in canonical settings, such as uniform distributions ($F^{\nu}_{s_i,\delta_i}$ uniform on $[0, \delta_i s_i \nu]$), and normal distributions ($F^{\nu}_{s_i,\delta_i}$ normally distributed on $[0, \nu]$ with mean $\mu = \delta_i s_i \nu$ and standard deviation $\sigma = \frac{\nu}{8}$). In a follow-up study (Cavallo & Jain, 2013) the authors consider a more limited setting in which the cumulative distribution function of the quality of submission depends only on the effort of the contestant and the value ν, and the winner is the contestant who submits the highest quality solution. They define the efficiency of a given equilibrium using the same approach:

$$E\left[\max_{i \in I} Q_i(\nu, \delta_i)\right] - \sum_{i \in I} \delta_i \tag{2}$$

They show that in any Nash equilibrium strategy profile (of the game between the contestants) the contestants collectively exert effort of less than or equal to P, the size of the prize. They then repeat the conditions (on the distributions) for an extreme-effort equilibrium to be efficient and show that under these conditions there exists a value ν for the organizer such that the winner-takes-all contest has no efficient equilibria. They also characterize a necessary condition for an extreme effort equilibrium to exist in which a given number of m contestants are active and the rest are inactive. For the case of a uniformly distributed quality they fully characterize the equilibrium for any prize level and any ν.

Mihm and Schlapp (2018) consider whether private or public feedback enhance the performance of contestants. They construct a two periods model of a contest in which the organizer may either grant no feedback, private feedback (observable only by the contestant) or public feedback (observable by all contestants) for each submission, between periods. A contestant decides how much effort to exert in the two periods based on the history of the game. At each period the quality of a submission is a function of the effort and a random shock. They show that in the unique perfect Bayesian equilibrium of the public feedback contest each contestant cares only about his relative performance. Moreover, in the perfect Bayesian equilibrium of the private feedback each contestant splits his expected effort equally between the two rounds and contestants with a moderate first-round performance exert substantial efforts in the second round, whereas contestants with a very high or very low first-round performance reduce their second-round efforts. When the organizer is interested in maximizing the quality of the best submission they characterize conditions under which the private feedback contest is optimal.

Giebe (2014) considers procurement innovation contests with an entry stage. Indeed, in many crowdsourcing contests platforms a registration stage takes place before the contest begins. Giebe models the entry stage as an auction mechanism to determine the participants in the contest and shows that it increases welfare. In his model there is a set of risk neutral sellers and one buyer. Seller i has an ability a_i which is her private information and is drawn from a cumulative distribution F with support $[\underline{a}, \bar{a}]$. Sellers produce innovation by exerting non observable efforts e_i at a linear cost $ce_i + \gamma$. Given her effort e_i, the quality of her submission is a realization of a random draw from the distribution $G^{a_i+e_i}$ on the support $\left[\underline{y}, \bar{y}\right]$. The power $a_i + e_i$ is seller i's research intensity, or, equivalently, her effective effort in the innovation contest. A higher $a_i + e_i$ implies a better innovation in the sense of first-order stochastic dominance. If the seller wins the contest her payoff is $\pi_i = p - ce_i - \gamma$ and if she looses it is $\pi_i = -ce_i - \gamma$. The buyer's (organizer's) payoff is the realized quality of the innovation minus the prize p. Alternatively the buyer may announce a first-score auction to determine the winner instead of a fixed prize p. In this case the contestants submit bids together with their innovation and the contestant with the highest score (quality minus price): $y_i - b_{i,1}$ wins the contest. Her payoff is then $b_{i,1} - ce_i - \gamma$. The organizer may also collect entry fees and exclude sellers from participation. This is done through an early entry auction. The organizer announces the number of contestants that will be allowed to participate in the contest n. Sellers then submit bids $b_{i,0}$ and compete over the spots at the contest. The n highest bidders are the contestants and they all pay the bidder $n+1$'s bid. The author's main result is a comparison between the fixed prize and the score auction. He shows that in equilibrium the two mechanisms are payoff equivalent in expectation for both the organizer and the contestants and are both welfare maximizers (i.e., maximize the overall expected payoff of participants).

One prominent conclusion that comes out of most of the papers reviewed in this subsection is that a single prize is usually the optimal prize structure. It is optimal under many different optimization functions for the organizer as well as under many different assumptions on the connection between effort and quality of a submission. However, it may not be optimal when consumers are sufficiently risk averse (Archak & Sundararajan, 2009), or in expertise contests where the quality of a submission is an additive function of the contestant's expertise and her effort (Terwiesch & Xu, 2008) or if the quality of a submission depends only on the contestant's ability and not on her effort (Ghosh & Kleinberg, 2014). There may be other situations in which a single prize will not be optimal that have not been explored yet. For example, we don't yet whether it is optimal when organizers compete over contestants, or in open contests.

2.2. Creativity and innovation

The understanding that contests may enhance creativity and innovation is not new. Earlier works in Economics have modeled innovation as a search process. The idea is that a contestant may conduct costly trials that have some probability of yielding a successful outcome one after the other or continuously. This fits well with the possibility to submit any number of submissions in a given contest in many of the crowdsourcing contests platforms. In this literature it is not the quality of the outcome that is uncertain but rather the time at which success will be obtained. Innovation is then achieved when contestants choose to conduct a large number of trials and the probability of a success increases. In the following subsection we present papers that examine the optimality of the contest not in terms of quality of submissions but rather in terms of innovation modeled as the probability of success in a series of costly trials.

Taylor (1995) models an innovation contest as a sequential search process. In each period a contestant chooses whether to conduct research. If she chooses to conduct research she pays a fixed cost and the outcome of her research is a single draw (privately observed by her) from a given distribution which is the same across contestants. Draws are independent across time and across contestants. The contestant's quality is then the highest outcome among the draws in periods in which she has conducted research up to a given period T. The contestant with the best outcome receives the prize. Taylor characterizes equilibrium in "stop-strategies" i.e., strategies in which a contestant conducts research in every period until her research outcome reaches some value and then she stops conducting research. The stopping value depends on the number of participating contestants and the size of the prize. The organizer's expected payoff is the collected entry fees plus the equilibrium expected value of the best innovation net of the prize. Taylor shows that under an optimally designed contest, the organizer restricts participation (invites only some of the contestants to participate) and extracts all expected surplus by charging an entry fee.

Choi (1991) models a contest in which contestants have imperfect information about the productivity or "hazard rate" of the R&D process. A success of another contestant at an intermediate stage may result in the uncertainty about the productivity of the effort being partially resolved. This may trigger an optimistic revision of beliefs about the difficulty of the task. This captures the well documented aspect of feedback (reviewed in Section 3.2.1 below) by which a good feedback to any of the contestants triggers the participation and resubmissions of many other contestants. In Choi (1991)'s model a contestant, at each moment of time, decides whether to continue the research at a flow cost of c or not. The value of successfully completing the process is V. The probability of success by time t is given by $1 - e^{-\lambda t}$, where λ is the "hazard rate," or conditional probability density of success, given no success to date. The parameter λ is unknown to the contestants and can either be high or low. The contestants have a prior belief that it is low with probability p. The contestants update their belief about λ as a function of time t, given that there has been no success up to t. Choi solves for the equilibrium behavior (in terms of stopping times) of two contestants with perfect observability (i.e., they observe not only whether they have succeeded but also whether their opponent succeeds at every stage) in a multi stage contest in which a success in several stages is needed for the success of the entire process. The author then shows that when there is no uncertainty about the hazard rates, one contestant's success is always bad for the other contestant, since it increases the technological gap between them. Under hazard rate uncertainty, there is another effect that a rival contestant's success can be a positive signal of success prospects.

Recently, Halac, Kartik, and Liu (2017) study contests that maximize innovation when contestant may learn about the innovation's feasibility and opponents' outcomes. Crowdsourcing contests often allow organizers to give feedback to contestants on their submissions. Feedback may be interpreted as a means of learning about the feasibility of the innovation. In their model the innovation's feasibility depends on a binary state (good/bad) that is unobservable. Time is continuous and goes from zero to T which is chosen by the organizer. At every moment t contestant i chooses an effort $a_{i,t}$ at instantaneous cost $ca_{i,t}$. A contestant's probability of success at every moment depends on whether the state is good or bad and on her effort. If the state is good it is $\lambda a_{i,t}$ for some $\lambda > 0$ and if the state is bad it is zero. if a success occurs at some moment, the organizer receives a utility of v. The organizer cares only about the first success, any other success will yield him a utility of zero. There is no discounting of time. At time t, given that no contestant had succeeded up to t, the public belief p_t, that the state is good is a Bayesian update of the prior belief p_0, and it decreases over time. A social welfare maximizing effort profile is such that all contestants exert effort $a_{i,t} = 1$ as long as $p_t \leq \frac{c}{\lambda v}$ and no effort afterwards. The organizer of the contest determines the duration T and a prize sharing scheme which is a tuple of functions $(w_i(s))_{i \in N}$ where $w_i(s)$ is the payment to contestant i (made at time T) when the vector of success times is s. The authors consider the winner-takes-all scheme in which all the amount is granted to the contestant that got the first success and the *equal-sharing* scheme in which all contestants that had a success share the prize equally. Moreover, they consider two disclosure policies by the organizer. The first is a *public* policy in which all information is disclosed at all times and the second is a *hidden* policy in which no information is revealed until the end of the contest. They first show that a winner-takes-all contest is optimal among *public* contests. In an optimal public winner-takes-all contest, each contestant uses a stopping strategy. The stopping time is increasing in p_0 and w (the size of the reward), decreasing in c and N, and non-monotonic in λ. Moreover, an *equal-sharing* contest is optimal among *hidden* contests. In an optimal hidden equal-sharing contest, there is an equilibrium in which each contestant uses a stopping strategy. Finally they characterize conditions under which the organizer prefers an optimal *hidden* contest to an optimal *public* contest.

Gross (2018) examines the effects of competition on creativity. Using data from logo design contests (the name of the website is undisclosed in the paper), and image comparison tools to measure originality, he finds that "competition has an inverted-U effect on creativity: some competition is necessary to induce contestants to produce radically novel, untested ideas over incrementally tweaking their earlier work, but heavy competition drives them to stop investing altogether". Encouraging creativity among contestants in design contests is therefore crucial for a better quality solution. Creativity is in fact experimentation and is therefore costly. Gross develops a game theoretic model in which the value of a submitted design for the sponsor is a function of its quality plus a random shock:

$$\nu_{jt} = ln(\beta_{jt}) + \varepsilon_{jt}$$

where β_{jt} is the quality of submission t by contestant j (a contestant can submit up to two submissions, and therefore $t \in \{1, 2\}$) and ε_{jt} is a random shock. Gross emphasizes the effect of the contest on the contestant's decision to considerably change her later submission and call such a decision creativity. The probability that contestant j will win the contest is given by

$$\frac{\beta_{j1} + \beta_{j2}}{\beta_{j1} + \beta_{j2} + \sum_{k \neq j} (\beta_{k1} + \beta_{k2})}$$

Players develop and submit designs one at a time, in turns, and immediately receive public feedback that reveals β_{jt}. When it is a given contestant's turn to submit a second design, she may choose one of three actions: 1. exploiting her previous design (making a small change), 2. exploring and creating a radically different design, or 3. balking from the contest. If the contestant "exploits", she submits a design of the same quality β_{j1} and pays a cost of $c > 0$. If she "explores" then with some probability q the new design will have a higher quality than the original design, i.e., $\beta_{j2} = \alpha \beta_{j1}$ for an exogenously given $\alpha > 1$, and with probability $1 - q$ the new design will be of a lower quality $\beta_{j2} = \frac{1}{\alpha} \beta_{j1}$. The cost of exploring is $d > c$. Assume that the expected quality as a result of exploring is higher than the quality of the first design i.e., $\left(qa + (1-q)\frac{1}{\alpha}\right)\beta_{j1} > \beta_{j1}$. Gross then identifies the conditions under which a contestant will choose any of the three actions as a function of a given level of competition $\mu = \sum_{k \neq j} (\beta_{k1} + \beta_{k2})$. Finally, he implements the model on the data using an in-house image comparison tool and measures the effects of feedback and competition on creative choices. He shows that when a contestant receives her first 5-star rating, her next design will be a near replica. The degree of similarity between the two designs (compared to other two designs where the first design did not receive a five star rating) increases by nearly 0.9 points, or three standard deviations. On the other hand, the presence of top-rated competitors reduce this effect by a factor of nearly two. He concludes that when competition is low, players choose between exploration and exploitation, whereas when competition is high, they choose between exploration and abandonment.

2.3. Selection of contests by players

A feature of platforms for crowdsourcing contests is that a given contestant may choose which contest or contests to participate in out of a large number of ongoing contests. This feature is usually absent from the classic contest theory literature in which a contest is studied as an isolated event. However, some recent papers have studied systems of multiple contests where players may choose between them.

DiPalantino and Vojnovic (2009) study a model in which players are endowed with different skill levels for the different contests, which are their private information. These skills are either contestant specific (each contestant is endowed with the same skill for all contests) or contest and contestant specific (a contestant may have different skill levels for different contests). Contests differ from one another in the size of the reward. In the first stage of the game, each contestant i selects a contest j and a bid (effort) b_{ij}. In the second stage, in each contest j, the prize is awarded to the contestant with the highest bid among those who selected the contest. For the contestant specific skill case, the authors explicitly find the symmetric equilibrium in mixed strategies in which a contestant participates with positive probability in a set of contests with the highest rewards. In equilibrium players are partitioned according to their skill levels. A contestant of skill level l mixes (i.e., participates with positive probability) on the set of top l reward contests. When the number of players goes to infinity the number of players that participate in a given contest is a Poisson random variable with a mean that depends on the size of the reward. For the contest-specific skill case, when the number of players grows to infinity, it is again shown that the number of players that participate in a given contest is a Poisson random variable with a specified mean.

Azmat and Moller (2009) present a theoretical model of a competition between two contests' organizers. Each contest's organizer i announces a prize structure $\nu_i = (\nu_i^1, \dots, \nu_i^n)$, $0 \leq \nu_i^k \leq \nu_i^{k-1}$ to be awarded to the highest quality submission (ν_i^1), second highest quality solution (ν_i^2) and so on, such that $\sum_{k=1}^{n} \nu_i^k = 1$. The contestants are identical, risk neutral, have linear cost of effort and each contestant can participate in, at most, one of the two contests. In such a setting with a single contest it is optimal to grant a single prize to the best quality submission. Given the prize structures (ν_1, ν_2), contestants choose which (if at all) of the contests to join. They then observe the number of participants in each contest and choose how much effort to exert. The probability that contestant n, who chose contest i when the set of contestants who chose contest i is given by N_i, of winning the first prize is given by

$$p_n^1 = \frac{(e_n)^s}{\sum_{j \in N_i} \left(e_j\right)^s}.$$

This is a Tullock contests success function as explained above. Conditional on contestant m winning the first prize, the probability that contestant n wins the second prize is given by

$$p_{n/m}^2 = \frac{(e_n)^s}{\sum_{j \in N_i - \{m\}} \left(e_j\right)^s}$$

and so on. The parameter $s \geq 0$ measures the accuracy of the contest's outcome w.r.t. players' efforts. The authors characterize the unique symmetric mixed strategy equilibrium (given the prize structures (ν_1, ν_2)) in which all contestants choose the first contest with a given probability and the second one with the remaining probability. Denote by $\bar{\nu}_i(m)$ the average of the m highest prizes in contest i. When $s \to 0$ the authors show that the expected number of participants in contest i is strictly larger than that in contest j if and only if $P^0(\nu_i) > P^0\left(\nu_j\right)$ where $P^0(\nu) = \sum_{m=1}^{N} \binom{N-1}{m-1} \bar{\nu}(m)$. Therefore, when s is very small a winner-takes-all contest attracts more participants than any other contest. When instead $s \to \infty$ the authors show that the expected number of participants in contest i is strictly larger than that in contest j if and only if $P^{\infty}(v_i) > P^{\infty}(v_j)$ where $P^{\infty}(v) = \sum_{m=1}^{N} \binom{N-1}{m-1} v^m$. When s is sufficiently large, a winner-takes-all contest attracts less participation than any other contest. Finally they discuss the symmetric equilibrium of the game between the contests' organizers (with the same budget) and show that if they aim to maximize the expected number of participants then when $s \to 0$ each organizer will award a single first prize, and when $s \to \infty$ each organizer will award $\frac{N+1}{2}$ identical prizes when N (the number of potential contestants) is odd or $\frac{N+2}{2}$ identical prizes when N is even. However, if the organizers aim to maximize equilibrium expected aggregate effort they will each award a single prize independent of s and N.

Korpeoğlu, Korpeoğlu, and Hafalir (2018a) consider M innovation contests' organizers and N contestants. Each contestant i develops a solution for each contest m with quality y_{im}. In this paper the focus is not on which contests will the contestants choose to participate in but rather on how much effort they exert at each of the contests given that they participate in all contests (non-exclusive case) or just in one (inclusive case). The quality of the solution is assumed to be a function of the contestant's effort (e_{im}) and of a realization of a (contestant and contest specific) random shock $\tilde{\xi}_{im}$. Therefore $y_{im} = r(e_{im}) + \tilde{\xi}_{im}$ where r is an increasing and concave function. Output shocks are i.i.d. with a cumulative distribution function H and a log-concave density function h on a finite support $[\underline{s}, \bar{s}]$. Contestant i's utility is defined over the vector of efforts $e_i = (e_{i1}, \ldots, e_{iM})$ she exerts and the vector of awards $x_i = (x_{i1}, \ldots, x_{iM})$ she receives. Contestant i's utility takes the form

$$U_i = \sum_{m=1}^{M} x_{im} - \mu\left(\sum_{m=1}^{M} \phi(e_{im})\right)$$

where μ is an increasing and homogeneous function of degree b and ϕ is an increasing and homogeneous function of degree p and the second term represents the contestant's cost of efforts. Each organizer chooses a single prize A_m which will be awarded to the contestant with the highest quality submission and she aims to maximize the expected quality of the highest quality submission. Therefore, the organizer's utility is given by

$$\Pi_m = \max_i y_{im} - A_m.$$

The authors first characterize a symmetric pure strategy equilibrium of the contestants' efforts given the prizes $(A_1, \ldots A_M)$. In this equilibrium all contestants exert the same effort in a given contest. They then assume that a coordinator (e.g. platform) determines the prizes in all contests and aims to maximize the expected average profit of the organizers: $\frac{1}{M}\sum_{m=1}^{M} \Pi_m$. They state the conditions on the functions μ and ϕ and on the parameters b and p such that the coordinator will determine a single award to be awarded in all contests and calculate this single award for different assumptions. Their main result is that when the contestant's output uncertainty is sufficiently large, the non-exclusive case (where contestants can exert effort in as many contests they want) yields a larger average profit for the organizers than the exclusive case (in which she can exert effort only in one contest). For the case where the organizers are strategic and interact in a game with each other (decentralized case) they show that when the uncertainty is high enough the average profit in the non-exclusive decentralized case is greater than in the exclusive centralized case.

The papers reviewed in this subsection take the first steps (using very different formulations of the problem) in shaping our understanding of behavior of both contestants and organizers in an environment with multiple contests. The first challenge is to study equilibrium behavior of contestants given multiple contests with different characteristics (e.g. different number and sizes of prizes, or the contestant's ability could be dependent on the specific contest). Once the equilibrium behavior is characterized the second challenge is to find an equilibrium of the game between organizers.

2.4. The platform

Surprisingly very few papers analyze the problem of a crowdsourcing platform seeking to maximize its profit. Wen and Lin (2016) examine the contest organizers' behavior given the fees charged by the platform and then solve for the optimal fees. They assume that the platform charges fees that are a function of the size of the prize that the organizer determines. In their model the contest organizer then maximizes

$$U(V) = \theta \cdot \max_{i \in N}\{Q(e_i)\} - V - K(V)$$

where N is the set of contestants, each contestant exerts an effort of e_i which results in a submission of a deterministic (increasing and quasi-concave) quality $Q(e_i)$ in equilibrium, V is the size of the reward the organizer determines for this contests, $K(V)$ are the fees that the platform charges and θ is the type of the organizer, which is her private information and is distributed according to a probability density function $g(\cdot)$ over an interval $[\underline{\theta}, \bar{\theta}]$. Each organizer therefore determines $V(\theta)$ that maximizes her revenue. The authors first examine the case of only one organizer (i.e., one contest) and show that the optimal crowdsourcing service fee, $K(V)$, is an increasing, concave function of the contest's prize. Therefore, the optimal schedule (a concave function with a decreasing marginal rate) encourages the high type organizers to choose a higher prize by charging them a lower rate. For the multiple organizers case the platform's problem is determining the optimal service fee mechanism that maximizes its revenue collected from all organizers:

$$\max_{K(V(\theta))} \int_{\underline{\theta}}^{\bar{\theta}} K(V(\theta))g(\theta)d\theta$$

under the incentive-compatibility constraint that for each θ and all $\eta \neq \theta$ reporting her true type to the platform is the organizer's best strategy:

$$\theta q(V(\theta)) - V(\theta) - K(V(\theta)) \geq \theta q(V(\eta)) - V(\eta) - K(V(\eta))$$

and the individual rationality constraint that for each θ participating as an organizer yields a non negative expected payoff:

$$\theta q(V(\theta)) - V(\theta) - K(V(\theta)) \geq 0$$

where $q(V) = \max_{i \in N}\{Q(e_i)\}$ is determined in the (contestants) equilibrium of a contest with the prize V. Asymptotic results are derived when the number of contestants N goes to infinity and it is shown that in this case, a system of T contests can be approximated by T independent contests, i.e., the expected top quality of a contest can be approximated by a function of its own prize. Therefore, for a platform with $N \to \infty$ contestants and T contests, the platform's profit maximization problem can be approximated by maximizing the sum of profits from T independent contests, each with N/T contestants. The optimal fee schedule can be approximated by the optimal fee schedule of an independent contest with N/T contestants and is therefore an increasing, concave function of the contest's prize.

3. Empirical research

The empirical research on crowdsourcing is growing rapidly, mainly due to ease of access to large data sets from the websites which conduct crowdsourcing contests. The main goal of these studies is to categorize and identify the incentives that affect the contestants' behavior in the crowdsourcing contests in the aim of designing better platforms for crowdsourcing contests. We organize this section according to the main empirical questions that have been studied in the empirical literature on crowdsourcing contests.

3.1. The effect of the size of the reward on participation and quality

Undoubtedly the question that had been most commonly researched in the empirical literature on crowdsourcing is whether a higher reward attracts more participants and whether this in turn leads to a higher quality of the winning solution. The evidence clearly show that a higher reward attracts more contestants especially in ideation contests, which primarily require creativity. However, the findings regarding whether quality improves with the number of submissions are inconclusive. In the theoretical contest theory literature the effect of increasing the number of participants in a contest on the expected quality of the winning submission is also not clear. It varies across models and depends on assumptions, such as whether contestants are risk averse, what form the contest success function takes, and whether the contestants pay an entry fee. It is therefore not surprising to learn that the empirical evidence is also diversified.

Araujo (2013) collected data from over 38,000 contests on "99Designs" and focused on factors affecting the quality of the submissions. In his paper quality is characterized by either success or failure where a contest is defined as a success if at least one high quality submission (rated 4 or 5 stars out of 5 by the organizer) was made. He finds that higher rewards do not translate to more effort by individual designers (measured by the number of submissions they made to the same contest). However, they attract more designers to the contest and this in turn is correlated with a higher quality of the winning design (or a better chance of getting high quality submissions).

Liu, Yang, Adamic, and Chen (2014) conduct a field experiment on "Taskcn" involving translation and programming contests. Their main goals were to study the effects of the size of the reward and a reservation value (in the form of an early submission of a given quality which they themselves submit) on the quality of submissions. They developed and ran 28 programming contests and 120 translation contests in three different treatments. Their main findings are as follows: 1. Tasks with high rewards receive significantly more submissions and submissions of a better quality than tasks with low rewards; 2. The quality of valid and best translation submissions[7] is significantly lower in the reserve treatments (with a high quality early submission made by the authors) than in the no-reserve treatments and 3. Experienced users submit their translations significantly later than inexperienced ones. The quality of a submission in their study was determined through evaluations made by experts.

Zheng, Xie, Hou, and Li (2014) examine data from design contests collected from "680.com", a Chinese crowdsourcing platform. They found that both solution quantity and solution diversity (variance of the solutions, the extent to which solutions are different from each other) had significant effects on solution quality (which was estimated by surveys sent to the contests' organizers after the contests had ended). Further, the size of the award had a significant impact on solution quantity but not on solution diversity. Therefore the effect of the size of the award on the quality was not clear. Finally, organizer-contestant interactions, in the form of feedback given by the organizers during the contest (also reported by organizers through surveys), significantly increased solution diversity but not solution quantity.

Yang, Chen, and Pavlou (2009) collect data from "Taskcn" and also find that a contest with a higher award will attract more solvers. They show that feedback increases the contestants' efforts and thus fixing the size of the award, if the organizer sends feedback to preferred solvers, an increase in the number of solvers is indeed a proxy measure of performance (quality). In the presence of feedback contestants tend to invest more effort and the quality of the winning submission out of a larger number of submissions, increases.

As opposed to the above papers, who find that higher rewards result in higher quality, Huang, Vir Singh, and Mukhopadhyay (2013) use data from "Threadless.com" and show that participants invest less effort as competition for the award increases and that increasing the reward may adversely affect the quality of the solutions. They argue that increased competition leads to reduced effort, which in turn leads to reduced quality.

Boudreau, Lacetera, and Lakhani (2011) examine data from 9661 software contests on "TopCoder" and show that when the number of contestants increases, greater competition reduces the incentive to exert effort but at the same time, increases the likelihood that at least one contestant will come up with an excellent solution. They show that a higher number of contestants increases overall contest performance for high-uncertainty problems, but may reduce it for low uncertainty problems. The level of uncertainty of a problem is defined as the number of problem domains upon which the solution has to draw. They evaluate the quality of submissions through scores that are generated via tests that were tailored-programmed for each problem. In Boudreau, Lakhani, and Menietti (2016) the authors again analyze data from "TopCoder", for 755 contests in which varying numbers of randomly assigned individuals competed to solve software algorithm problems. They show that contestants with the lowest ability have little response to an increase in the number of contestants, contestants with intermediate ability responded negatively (decreased effort), and contestants with the highest ability responded positively by increasing their effort. The ability of a contestant is estimated through a skill rating that each contestant receives on TopCoder. This skill rating is a public, numeric rating based on the history of her submissions and it reveals the contestant's position within the overall skill distribution of programmers on the platform.

In addition to the size of the reward, the effect of other characteristics of the contest on the number and quality of submissions has been empirically investigated. Shao, Shi, Xu, and Liu (2012) examine data on software development tasks, collected from "zhubajie.com", a Chinese crowdsourcing platform. They tested the effects of the following parameters on the number of contestants and the ability of the winner in a given contest: the size of the reward, the contest duration, the average reward in other contests in the same category (the "market price"), the number of other projects in the same category (the "competition intensity"), the number of solvers, and the difficulty level of the task. They show that the competition intensity, the size of the reward, the contest duration and the difficulty level all have significant effects on the number of contestants. More specifically, a task that is characterized with a higher reward, less difficulty, longer duration and fewer competing projects will attract more solvers. Moreover, competition intensity, market price, reward size, and difficulty level all have a significant influence on the winner's ability level; higher rewards and higher difficulty levels lead to higher ability levels of winners. In conclusion, high ability contestants are drawn to competitive tasks.

Walter and Back (2011) study empirically the effect of a list of factors which they term "external" and include the size of the reward, the contest duration, the description of the task (how much detailed is it, its length and clarity), how specific the task

[7] The quality of a translation submission was determined by a group of experts. A translation was labeled "not valid" if it was determined to be a machine made translation or an imitation of an earlier submission (submissions are open).

is, and the brand-strength of the seeker, on the number and quality of submissions in innovation contests. They use data from "Atizo.com", a platform for the development of new products and services through contests. On "Atizo.com" only the size of the total reward is announced but the organizer of a contest may choose up to five winners and distribute the prize among them. The main result of the study is that the external factors that have significant effects on the amount of submissions are different from those that affect the average quality of rated ideas. They show that the size of the reward affects the amount of ideas (submissions) but not their average quality. Moreover, high rewards may result in large numbers of solver submissions, but they are often of lower quality. Furthermore, some factors, such as the task description and the contest duration, have no effect on the average quality of submissions.

Chen, Pavlou, and Yang (2014) also investigate the effect of a wide range of project properties on the number of participants in a contest. They divide the properties into 3 categories: (1) contest design parameters (prize, duration, description length); (2) market environment factors (competition intensity: the number of overlapping contests; market price: the average prize across competing contests) and (3) project intrinsic characteristics (project complexity and project type). The project's type is defined as ideation (requiring primarily creativity) or expertise. The project's complexity is measured by the incompletion rate and the submission speed. They analyze data from 3723 contests on "Taskcn" in which the average number of contestants in a contest is 111.67. Their main findings are that ideation-based contests are very sensitive to the monetary incentive (prize), much more so than the expertise-based contests. Moreover, longer project descriptions result in fewer contestants for ideation-based contests. Finally, market environment factors also show different effects across project types. Expertise-based contests are very sensitive to competition intensity. On the other hand, a higher number of overlapping contests does not reduce participation in ideation-based contests. Ideation contests are also much more sensitive to the market price.

Wang, Tian, and Xu (2015) analyze the effects of different characteristics of the design task on the performance of the contestants. They use data from "studio.Topcoder" and show that a longer contest duration increases performance in one-stage contests. Moreover, they show that more detailed task descriptions reduce the performance in one-stage contests, but increase the number of solvers in two-stage contests. In a two-stage contest, the organizer receives a set of solutions in the first round and then provides feedback to the solvers so that they can improve the quality of their final solution and reduce the risk; in the second round the solvers submit their updated solutions. Finally they demonstrate that the incentive effect of the size of the first prize is stronger in one-stage contests than in two-stage contests, while the incentive effect of the size of the second prize is stronger in two-stage contests than in one-stage contests.

3.2. *Contestants' strategies*

Another line of empirical research on crowdsourcing contests addresses the question of identifying the strategies of the contestants. The timing strategy - the point at which contestants choose to submit their solution in a contest - is widely studied, as is the contestant's number of submissions at a given contest. As before, evidence as to whether early or late submissions have a higher probability of winning are inconclusive. However, most of the research reviewed here shows that experienced contestants tend to submit earlier in the contest. Several authors also study the contestants' strategy in response to their and their opponents' reputation and whether contestants choose to "copy" other contestants solutions in open contests. Moreover, the effect of feedback given by organizers, on following contestants' behavior is studied intensively (as reviewed in Section 3.2.1 below). The theoretical literature on innovation and creativity identifies contradicting effects that may arise from feedback - a positive effect (the task is feasible) and a negative effect (the other contestant is already succeeding). The empirical literature mostly finds the effect of feedback to be positive.

Al-Hasan, Hann, and Viswanathan (2015) examine data from a design website (the website's name is not revealed) and study the timing of submissions. They observe a possible trade-off between a late submission, which allows the contestant to observe and react to other players' submissions and the feedback that these submissions receive, and an early submission that will allow more feedback on their own submission from the organizer. The authors show that both early and late submissions have a higher chance of winning compared to intermediate submissions. They also demonstrate that open innovation contests have informational spillover relating to submissions that benefit later entrants compared to closed contests. In other words, in an open contest entrants are able to learn from the feedback given to early submissions while in a closed contest they have to submit early if they wish to get feedback. Finally, they show that the more detailed the feedback the higher the chance that a later entrant will win the contest (again indicating information spillover). They conclude that blind contests could promote greater variety by reducing information spillover from earlier submissions. Their dataset includes 16,645 contests, out of which 79% are open contests and the rest are closed (blind).

Archak (2010) analyzes the strategic behavior of contestants on "TopCoder" where contests are blind (or simultaneous). He examines the reputation system used by the website and its effects on the behavior of the contestants. At TopCoder each submission is reviewed by three reviewers and gets a score. The entire prior competition history of a contestant is summarized via a relatively complex formula which yields a single rating number. Archak starts by showing that an individual's rating is a significant predictor of future performance and then shows that high-rated contestants move first in the registration phase in order to signal to other high-rated contestants that they should not participate in this contest (creating a deterrence effect). Contestants with higher reputations enjoy more freedom in the project choice phase and can successfully deter entry of their opponents in the same contest. The dataset included 1,966 software design contests and 1,722 software development contests run by TopCoder.

DiPalantino, Karagiannis, and Vojnovic (2011) study individual as well as collective behavior of contestants in crowdsourcing contests using data from "Taskcn". They show that individual contestants tend to participate in contests with a specific range of monetary prizes, which, according to the authors, reflect the contestant's skill level. Moreover, they find that the median of participation is roughly one submission per week per contestant. Contestants participate in a "bursty" manner with a median of less than a day between subsequent submissions (mean of four days). The community as a whole spreads more evenly across the entire range of rewards. However, they show (as other studies have shown) that higher rewards attract more contestants and this effect diminishes with the size of the reward. An interesting aspect of this work is that the authors use a novel approach to describe the competition between participants. They form a network in which each node is a contestant and an edge between two contestants is formed when they both compete for the same task (contest). They then examine centrality measures on this network and conclude that contestants who direct their effort to tasks with a larger number of contestants tend to make smaller revenue and contestants who tend to compete with a wider variety of different contestants tend to make a larger revenue. Finally, they also analyze the importance of experience on the success of a contestant. Their analysis implies that contestants improve over time; yet, most of this improvement appears to occur after their first few submissions. This study data includes around 17,000 contests with 1.7 million submissions over a four year period.

Zhang, Vir Singh, and Ghose (2016) study the effect of the participation of a "superstar" contestant on the subsequent success of other contestants. They analyze data from "TopCoder" and show that an individual's probability of winning in subsequent contests increases significantly after she has participated in a contest with a superstar coder. They term this effect a learning effect. They suggest that individuals should be encouraged to participate in contests with superstars early on as it can lead to significant progress along the learning curve leading to a higher number and quality of submissions per contest. A superstar in their paper is defined as a contestant with a very high rating (over 2200), calculated by "TopCoder", based on performance history. At TopCoder contestants can observe the ratings of all other registered contestants to the same contest at the registration phase.

Bockstedt, Druehl, and Mishra (2016) explore the behavior of 2623 contestants in open design contests on "Logomyway". In an open contest, where all submissions are visible by all other participants, a contestant must weigh the costs of revealing her submission against the benefits of improving her submission through emerging information and feedback. On "Logomyway" the organizer of a contest may give ranks to submissions and/or tag the submissions with the words: "Elements we like". The authors analyze the submission behavior of the contestants in terms of three dimensions: the timing of the first submission by the contestant, the number of submissions the contestant makes to a particular contest, and the length of active participation in a given contest by the contestant. They show that contestants who submit their first submission early are more likely to succeed in the contest. Moreover, they show that increasing the length of participation in a contest has a positive effect on a contestant's likelihood of success.

Hofstetter, Nair, and Misra (2018) study another important aspect of open contests by which contestants observe others submissions and may copy them (with or without making minor changes). They analyze data gathered from crowdspring.com and compare images using image comparison algorithms. They show that contestants who enter later into contests tend to imitate better rated designs that are submitted prior to their entry, thereby generating significant risk to early entrants that their ideas will be replicated. However, they also find that organizers tend to reward original early designs, and avoid picking as winners those that seem to be plagiarizing and free-riding. They conclude that market behavior on open crowdsourcing platforms may have a self-policing component that disincentives excessive imitation, rewards originality and prevents unraveling.

3.2.1. Feedback

Many of the crowdsourcing contest platforms allow the organizer of a contest to give feedback in different forms on the submissions. These may either be free style, where she can write any comment, or one of a given small set of available tags or numeric rankings. Feedback has a large impact on contestants' behavior as was already mentioned in many of the above studies. Moreover, it is usually an important factor in a contestant's decision to submit her solution early. This aspect of the crowdsourcing contests has received a lot of attention from empirical researchers in the last few years. All of the papers we review below find a significant effect of feedback on qualities and numbers of submissions. This effect is mostly positive. Feedback in early stages of the contest attract more contestants and increase the effort and quality of submissions. The only negative impact of feedback is that it may reduce innovation/experimentation or the variance of subsequent submissions but the evidence are ambiguous whether this indeed happens or not.

Jian, Yang, Ba, Lu, and Jiang (2016) collect data on 1031 logo design contests from "99designs". They find that providing in-process feedback sends an effective signal of a contest holder's intention to pay (on "99designs" not all contests are guaranteed to end with a winner - the contest holder may refuse to choose a winner) and therefore attracts an increased number of submissions. Moreover, they show that in-process feedback exhibits diminishing returns of value and experienced contestants are more responsive to early feedback made by organizers than inexperienced contestants.

Wooten and Ulrich (2017) examine also the effect of feedback in design contests. They conduct a set of field experiments using two online contest websites to compare the performance of three different feedback treatments – no feedback, random feedback (i.e., Information provided to the contestant on the quality of an idea which is largely uncorrelated with the organizer's quality function), and directed feedback (i.e., feedback to the contestant on the quality of her submission that directs her towards what the organizer is looking for and is highly correlated with the organizer's quality function). They find that while directed feedback improves the average quality of submissions (as evaluated by experts), it does not have this effect on the quality of the best submission. No feedback or random feedback may produce a better top-end submission than directed feedback. Moreover, as could be intuitively expected, directed feedback reduces the variance in submission quality by directing the submissions to the desired outcome.

Boudreau and Lakhani (2015) analyze the optimal disclosure policy (by the organizer) in an innovation contest. They conduct several contests on "TopCoder" for solving the same problem (a computational biology problem) with the same number and composition of contestants and imply different disclosure policies. In some of the contests the contestants are informed during the contest on their intermediate progress while in others they are only informed at the end. They show that intermediate disclosure has the advantage of encouraging contestants to improve their existing solution, but also has the effect of limiting experimentation. They analyze the comparative advantages of intermediate versus final disclosure policies in fostering innovation.

Jiang, Huang, and Beil (2016) collected data on logo design contests. They constructed a discrete time model of a contest. In each period t, there is a set of potential entrants and a set of incumbent contestants. The organizer commits to the full feedback policy (i.e., he provides feedback at the end of each period) and announces a reward R. In the first period the potential entrants arrive at the contest, and decide whether to submit a design. The organizer evaluates the submitted designs and announces the ratings of submissions. The rating is on the scale of 1–5 stars. At the beginning of each of the subsequent periods, incumbents and potential entrants observe all existing ratings. Based on this information, potential entrants decide whether to join the contest and incumbents choose whether to submit a new design or revise their submitted design (or do both or none). Each of these decisions is endowed with a cost. In period $T+1$, the contestant with the best quality design wins the contest and receives the prize. The authors assume (based on observed data) that each contestant is affected only by her own ratings. They describe the Markov Perfect equilibrium of the game and use the data to estimate the parameters of the game observing the contestants behavior. They show that their model not only fits well with the data but gives accurate prediction for behavior of contestants in contests. Finally the authors use the model to run simulations of four different feedback policies: full/early/late/no feedback. Their results reveal that the maximum quality achieved is higher in the full feedback and the late feedback policies than in the no feedback and the early feedback policies. They conclude that if the organizer's objective is to maximize the number of top creators who achieve high ratings (5-star), or to maximize the total number of contest participants, the late feedback policy is in fact a better option than the full feedback policy.

Deck and Kimbrough (2017) test the predictions of Halac, Kartik and Liu (2017) by running an experiment on innovation contests when success may not be feasible and contestants may learn from each other. The organizer of the contest can vary the prize allocation rule from winner-takes-all in which the first successful contestant receives the entire prize to *Shared* in which all successful contestants during the contest duration share the prize equally. The designer can also vary the information disclosure policy from *Public* in which at each period, all information about contestants past successes and failures is publicly available, to *Private*, in which contestants only know their own histories. Their results are that *Private* contests behaviorally dominate *Public*, regardless of the prize allocation rule, and moreover, that *Shared,* and *Private* contests dominate winner-takes-all, and *Private* contests.

Gross (2017) collected data on 4294 commercial logo design contests, and showed that feedback reduces participation but improves the quality of subsequent submissions, with an ambiguous effect on high-quality output. Gross uses his theoretical model (developed in Gross, 2018) to evaluate the cost of effort exerted by contestants and the innovation of new submissions compared to earlier submissions. He concludes that feedback increases the number of high-quality ideas produced and is thus desirable for a principal seeking innovation.

3.3. Who are the winners in the contests?

One of the observations made in most empirical papers on crowdsourcing is that a very small number of contestants win the majority of the contests as described in the following papers. Yang, Adamic, and Ackerman (2008) examine the behavior of contestants on “Taskcn”. They find significant variation in the expertise and productivity of the participating users: a very small core of successful users contributes nearly 20% of the winning solutions on the site. They also provide evidence of strategic behavior among the core participants, in particular, picking tasks with a lower expected level of competition. Araujo (2013) analyzes the distribution of designers per contest and the distribution of awards won per designer on “99Designs”. He shows that a small proportion of designers win almost all the contests. Baba, Kinoshita, and Kashima (2016) show that more than 80% of the contestants who participated in contests on “Lancers.jp” have participated in less than 10 contests, and that more than 90% of them have never won any contest. In addition, among the contestants who have participated in more than 10 contests, the top 25% represent 90% of contest winners. They propose a statistical model of crowdsourcing and develop a contest recommendation system that estimates the probability of winning for a specific contestant and recommends which contest to participate in.

Khasraghi and Aghaie (2014) examine the participation history of contestants on “TopCoder”. They collect data on each contestant’s participation frequency, participation recency, winning frequency, winning recency and last performance and show that these factors significantly influence the contestant’s current performance. In particular, the results show that competitors’ participation frequency and winning frequency moderate the relationship between their last performance and their current performance. In other words, a more frequent contestant and one that has won more contests is more likely to win future contests as well.

Yang, Chen, and Banker (2010) collect data from 7728 contest projects on “Taskcn”. They show that winning experience is a good predictor of future winning propensity: a contestant with more winning experiences is more likely to win in the future. Moreover, they show that very early submissions and very late submissions have higher probability of winning than those in-between. Finally they show that different types of contests appear to attract solvers with different expertise. In ideation-based projects (such as naming projects), higher rewards and longer duration result in a distribution of contestants with less experience while for expertise-based projects (e.g. software development), the award size has no significant effect on the expertise variation across contestants.

4. Open problems in crowdsourcing contests

As emphasized in this review crowdsourcing contests have features that distinguish them from the previously existing models for contests, such as an uncertain number of participants, multiple-round feedback, and the fact that participants are active on a platform on which many crowdsourcing tasks may be chosen from. This survey thus considers the literature that particularly addresses crowdsourcing contests and their specific characteristics. The interplay of theoretical and empirical work is highly important in the study of crowdsourcing contests. Theoretical research may be motivated by empirical results and may in turn motivate empirical study. One way to overcome the existing gap between the theoretical and empirical research is by conducting smaller scale lab experiments or using simulations. In this section we highlight what we believe are the main open questions in the study of crowdsourcing contests.

Platforms. We believe that platforms must be introduced as players in the crowdsourcing contests game. There are already many platforms for crowdsourcing contests and their survival depends on the rules they use and their ability to attract good contestants and many organizers (initiators of the contests). Theoretical as well as empirical research that will help us understand how can they achieve this goal is essential. Each of the existing crowdsourcing platforms has its own unique characteristics (e.g. possible formats and rules of contests, one-stage vs. two-stage contests, and money back guarantees). This richness creates new and interesting challenges for the theory to tackle. Moreover, platforms use recommendation systems to recommend contests to participants. Understanding how to assign contestants efficiently into contests is thus also a challenge for platforms as well as researchers.

Competition among contests. Crowdsourcing platforms give us a unique opportunity to examine an economy in which organizers compete over the attention of possible contestants. We may also observe how the contestants choose which contests to join. The theoretical challenge is therefore to describe such an economy and understand the behavior of both the organizers and the contestants. We presented some results in this direction on Section 2.3. However, many aspects of this environment are still unexplored. Empirical evidence on what motivates the contestants is already abundant, however, the organizers’ behavior has not yet been analyzed, e.g., how do they choose their prize amount, the winner (especially since most of the time the organizers are not experts who can accurately evaluate the solutions) and other attributes of their task or contest, given their budget and time constraints.

Information disclosure andReputation. Information disclosure in crowdsourcing contests is usually done through feedback and reputation systems. While feedback received attention mostly from the empirical literature, reputation systems have not received any. Almost all crowdsourcing platforms use a reputation system. A contestant achieves reputation according to how many contests and prizes she won. What is the role of reputation? How does it affect the contestants’ behavior? For example, some platforms (e.g. “99designs”) allow the organizer to make her contests into a “high level” contest by which she offers a high prize (above some minimal value specified by the platform) and then only contestants with high reputation may enter the contest. Who are the organizers who choose these form of contests? How do the contestants with high reputation choose whether to join such a contest or a "regular" one? These are questions that call for both empirical and theoretical study.

Open vs. Closed contests.Submissions in many crowdsourcing contests platforms are sequential or open. A contestant makes a submission after observing the submissions of other contestants. In some platforms it is the contestant's decision whether to submit openly or blindly. How does the open nature of the contest affect the contestants decisions to enter a contest and the effort they exert. As described in this survey, the few theoretical as well as empirical results we have so far suggest that closed contests dominate open ones. Therefore it is still a riddle why is it used in reality.

Contestants. Although the main concern of almost all papers in this review is the behavior of contestants in crowdsourcing contest there still exists a gap between the theoretical and empirical research. Empirical research concentrated on contestants' strategies in terms of timing of their submissions during the contest, their response to their own and others' feedback and the number of submissions they submit at a contest. These questions have received almost no attention in the theoretical research. Moreover, as is well documented in the empirical literature the vast majority of contestants in the contests never win a prize. What then motivates these contestants? How much effort do they exert? These are also questions yet to be addressed by theory.

References

Al-Hasan, A., Hann, I., & Viswanathan, S. (2015). *Information spillovers and strategic behaviors in open innovation crowdsourcing contests: An empirical investigation*. Working paper.
Ales, L., Cho, S., & Korpeoğlu, E. (2017). Optimal award scheme in innovation tournaments. *Operations Research, 65*(3), 693–702.
Araujo, R. (2013). 99designs: An analysis of creative competition in crowdsourced design. In *Proceedings of the first AAAI conference on human computation and crowdsourcing*.
Archak, N. (2010). *Money, glory and cheap talk: Analyzing strategic behavior of contestants in simultaneous crowdsourcing contests on topcoder.com*. WWW 2010.
Archak, N., & Sundararajan, A. (2009). Optimal design of crowdsourcing contests. In *Proceedings of the thirtieth international conference on information system, ICIS 2009*.
Azmat, G., & Moller, M. (2009). Competition among contests. *RAND Journal of Economics, 40*(4), 743–768.
Baba, Y., Kinoshita, K., & Kashima, H. (2016). Participation recommendation system for crowdsourcing contests. *Expert Systems With Applications, 58*, 174–183.
Bockstedt, J., Druehl, C., & Mishra, A. (2016). Heterogeneous submission behavior and its implications for success in innovation contests with public submissions. *Production and Operations Management, 25*(7), 1157–1176.
Boudreau, K., Lacetera, N., & Lakhani, K. (2011). Incentives and problem uncertainty in innovation contests: An empirical analysis. *Management Science, 57*(5), 843–863.
Boudreau, K., & Lakhani, K. (2015). "open" disclosure of innovations, incentives and follow-on reuse: Theory on processes of cumulative innovation and a field experiment in computational biology. *Research Policy, 44*, 4–19.
Boudreau, K., Lakhani, K., & Menietti, M. (2016). Performance responses to competition across skill levels in rank-order tournaments: field evidence and implications for tournament design. *The RAND Journal of Economics, 47*, 140–165.
Cavallo, R., & Jain, S. (2012). Efficient crowdsourcing contests. In *Proceedings of the 11th international conference on autonomous agents and multi-agent systems (AAMAS 2012)*.
Cavallo, R., & Jain, S. (2013). Winner-take-all crowdsourcing contests with stochastic production. In *Proceedings of the first AAAI conference on human computation and crowdsourcing* (pp. 34–41).
Che, Y. K., & Gale, I. (1998). Caps on political lobbying. *American Economic Review, 88*(3), 643–651.
Chen, P., Pavlou, P., & Yang, Y. (2014). *Determinants of open contest participation in online labor markets*. Working paper
Choi, J. P. (1991). Dynamic r&d competition under 'hazard rate' uncertainty. *RAND Journal of Economics, 22*(4), 596–610.
Clark, D., & Riis, C. (1998). Contest success functions: an extension. *Economic Theory, 11*(1), 201–204.
Corchón, L. (2007). The theory of contests: a survey. *Review of Economic Design, 11*, 69–100.
Deck, C., & Kimbrough, E. (2017). Experimenting with contests for experimentation. *Southern Economic Journal, 84*(2), 391–406.
DiPalantino, D., Karagiannis, T., & Vojnovic, M. (2011). Individual and collective user behavior in crowdsourcing services. In *Technical report MSR-TR-2010-59, microsoft research*.
DiPalantino, D., & Vojnovic, M. (2009). Crowdsourcing and all-pay auctions. *Proceedings of the 10th ACM conference on Electronic commerce (EC 09)* (pp. 119–128).
Ewerhart, C. (2015). Mixed equilibria in tullock contests. *Economic Theory, 60*(1), 59–71.
Gallice, A. (2017). An approximate solution to rent-seeking contests with private information. *European Journal of Operational Research, 256*, 673–684.
Gao, A., Bachrach, Y., Key, P., & Graepel, T. (2012). Quality expectation-variance trade-offs in crowdsourcing contests. In *Proceedings of the twenty-sixth AAAI conference on artificial intelligence*.
Ghosh, A., & Hummel, P. (2012). *Implementing optimal outcomes in social computing: A game-theoretic approach*. WWW 2012.
Ghosh, A., & Hummel, P. (2015). *Cardinal contests*. WWW 2015.
Ghosh, A., & Kleinberg, R. (2014). Optimal contest design for simple agents. *Proceedings of the fifteenth ACM conference on Economics and computation (EC 14)* (pp. 913–930).
Giebe, T. (2014). Innovation contests with entry auction. *Journal of Mathematical Economics, 55*, 165–176.
Gross, D. (2017). Performance feedback in competitive product development. *RAND Journal of Economics, 48*(2), 438–466.
Gross, D. (2018). *Creativity under fire: The effects of competition on creative production*. NBER Working Paper No. 25057.
Halac, M., Kartik, N., & Liu, Q. (2017). Contests for experimentation. *Journal of Political Economy, 125*(5), 1523–1569.
Hillman, A., & Riley, J. (1989). Politically contestable rents and transfers. *Journal of Public Economics, 34*(2), 129–142.
Hillman, A., & Samet, D. (1987). Dissipation of contestable rents by small numbers of contestants. *Public Choice, 54*(1), 63–82.
Hofstetter, R., Nair, H. S., & Misra, S. (2018). *A copycat penalty: Micro evidence from an online crowdsourcing platform*. Working paper
Huang, Y., Vir Singh, P., & Mukhopadhyay, T. (2013). How to design crowdsourcing contest: A structural empirical analysis. In *Proceedings of the conference on information systems and technology, CIST 2012*.
Jian, L., Li, Z., & Liu, T. X. (2014). *Competing openly or blindly in crowdsourcing contests?*. Working paper
Jian, L., Yang, S., Ba, S., Lu, L., & Jiang, C. (2016). *Understanding the impact of uncertainties on crowdsourcing contest participation*. Working paper.
Jiang, Z., Huang, Y., & Beil, D. (2016). *The role of feedback in dynamic crowdsourcing contests: A structural empirical analysis*. Working paper.
Khasraghi, H. J., & Aghaie, A. (2014). Crowdsourcing contests: understanding the effect of competitors' participation history on their performance. *Behaviour & Information Technology, 33*(12), 1383–1395.
Konrad, K. (2009). *Strategy and dynamic in contests*. Oxford University press.
Korpeoğlu, E., & Cho, S. H. (2018). Incentives in contests with heterogeneous solvers. *Management Science, 64*(6), 2709–2715.
Korpeoğlu, E., Korpeoğlu, C., & Hafalir, I. (2018a). *Parallel innovation contests*. Working paper
Korpeoğlu, E., Korpeoğlu, C., & Tunc, S. (2018b). *Optimal duration of innovation contests*. Working paper
Liu, T. X., Yang, J., Adamic, L. A., & Chen, Y. (2014). Crowdsourcing with all-pay auctions: A field experiment on taskcn. *Management Science, 60*(8), 2020–2037.
Ludwig, S. (2006). *Private information in contests - sequential versus simultaneous contests*. Working paper.
Mao, K., Capra, L., Harman, M., & Jia, Y. (2017). A survey of the use of crowdsourcing in software engineering. *The Journal of Systems and Software, 126*, 57–84.
Mihm, J., & Schlapp, J. (2018). Sourcing innovation: On feedback in contests. *Management Science, 65*(2), 559–576.
Moldovanu, B., & Sela, A. (2001). The optimal allocation of prizes in contests. *American Economic Review, 91*, 542–558.
Moldovanu, B., & Sela, A. (2006). Contest architecture. *Journal of Economic Theory, 126*, 70–96.
Morgan, J. (2003). Sequential contests. *Public Choice,, 116*, 1–18.
Nitzan, S. (1994). Modeling rent seeking contests. *European Journal of Political Economy, 10*(1), 41–60.
Segev, E., & Sela, A. (2014). Multi-stage sequential all-pay auction. *European Economic Review, 70*, 371–382.
Shao, B., Shi, L., Xu, B., & Liu, L. (2012). Factors affecting participation of solvers in crowdsourcing: an empirical study from china. *Electronic Markets, 22*, 73–82.
Sisak, D. (2009). Multiple prize contests – the optimal allocation of prizes. *Journal of Economic Surveys, 23*(1), 82–114.
Stouras, K. (2017). *Crowdsourcing contests with private types and evaluation uncertainty*. Working paper.
Stouras, K., Hutchison-Krupat, J., & Chao, R. (2017). *The role of participation in innovation contests*. Working paper.
Taylor, C. R. (1995). Digging for golden carrots: An analysis of research tournaments. *American Economic Review, 85*(4), 872–890.
Terwiesch, C., & Xu, Y. (2008). Innovation contests, open innovation, and multiagent problem solving. *Management Science, 54*(9), 1529–1543.
Tullock, G. (1980). Efficient rent seeking. In J. M. Buchanan, R. D. Tollison, & G. Tullock (Eds.), *Toward a theory of the rent-seeking society*. Dallas: Texas A & M University Press.
Vojnovic, M. (2015). *Contest theory*. Cambridge University press.
Walter, T., & Back, A. (2011). *Towards measuring crowdsourcing success: An empirical study on effects of external factors in online idea contest*. Working paper.

Wang, L., Tian, J., & Xu, Y. (2015). *Relationship between design elements and performance in online innovation contests: Contest sequence is moderator?" WHICEB 2015 proceedings*.

Wen, Z., & Lin, L. (2016). Optimal fee structures of crowdsourcing platforms. *Decision Sciences, 47*(5), 820–850.

Wooten, J., & Ulrich, K. (2017). Idea generation and the role of feedback: Evidence from field experiments with innovation tournaments. *Production and Operations management, 26*(1), 80–99.

Xu, H., & Larson, K. (2014). Improving the efficiency of crowdsourcing contests. In *Proceedings of the 13th international conference on autonomous agents and multi-agent systems (AAMAS 2014)*.

Yang, J., Adamic, L., & Ackerman, M. (2008). Crowdsourcing and knowledge sharing: Strategic user behavior on taskcn. In *Proceedings of the EC 2008*.

Yang, Y., Chen, P., & Banker, R. (2010). Impact of past performance and strategic bidding on winner determination of open innovation contest. In *Proceedings of the workshop on information systems and economics, St. Louis 2010*.

Yang, Y., Chen, P., & Pavlou, P. (2009). Open innovation: An empirical study of online contests. In *Proceedings of the thirtieth international conference on information system, ICIS 2009*.

Yuen, M., King, I., & Leung, K. (2011). A survey of crowdsourcing systems. In *Proceedings of the IEEE international conference on privacy, security, risk, and trust, and IEEE international conference on social computing*.

Zhang, S., Vir Singh, P., & Ghose, A. (2016). *A structural analysis of the role of superstars in crowdsourcing contests*. Working paper.

Zhao, Y., & Zhu, Q. (2014). Evaluation on crowdsourcing research: Current status and future direction. *Information Systems Frontiers, 16*, 417–434.

Zheng, H., Xie, Z., Hou, W., & Li, D. (2014). Antecedents of solution quality in crowdsourcing: The sponsor's perspective. *Journal of Electronic Commerce Research, 15*(3), 212–224.