Abstract

Rankings and tournaments are often used to incentivize task completion and participation in online innovation and design contests and prediction markets. One of the main challenges for platform operators is to encourage high quality contributions and effort. In this study we illustrate that in such tournaments, the participants’ ranks interfere with risk taking behavior. We present an online experiment accompanying the FIFA World Cup 2014, considering the interplay of different tournament modes (individual and team rankings), the relative rank, tournament progress, and risk taking. We find that subjects take higher risk as the tournament progresses, where this increase is stronger for subjects competing individually, compared to those competing as teams.

1. Introduction

Electronic markets are developing rapidly. New and IT-enabled business models, features, and standards arise, as for instance recommender systems and crowdsourcing platforms. Such platforms use the input of workers all over the globe to co-create value. There are several types of such platforms with different aims – prediction markets aim to forecast uncertain events [37], innovation contests are generating creative solutions for a given problem [58], design contests are used to create aesthetic and meaningful graphical designs [2], and crowdsourcing platforms such as Amazon Mechanical Turk (AMT) try to outsource “manual” tasks or are being used for experimentation [46], as a promising and low cost tool for business and research. Howe [33] first defined crowdsourcing as “the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call.” In the past years, companies have initiated many crowdsourcing activities to benefit from the knowledge, creativity, skill, and working hours potential of these open crowds [58]. Moreover, crowdsourcing can lead to a reduction in research and development costs since compensation is comparatively low. Lastly, crowdsourcing typically generates solutions fast, as response times are short [42, 46] – someone is always up for work.

One dimension of crowdsourcing is given by the incentive schemes [36]. The most common types here are fixed piece rates and tournaments [56].

In tournaments, companies usually only pay for satisfying solutions. Therefore they face essentially no risk of failure.

The principle of such tournaments can be briefly summarized as follows: Typically, a task and a set of rewards are announced to attract potential workers who then compete against each other in completing the task. Over the course of the tournament, a ranking informs the participants about their current performance evaluation and (or just) their position in the ranking – the information relevant for payoff. The most successful contributors in the eyes of the issuer or an external jury win a (graduated) set of rewards. Such schemes are often thought of a supporting element to motivate (continued) participation, whereas there is also evidence that introducing competition or even any rewards at all can also have detrimental effects, especially for creativity-centered tasks [22, 23].

Moreover, crowdsourcing may be differentiated with respect to whether and how the workers are grouped. In order to harness potentially beneficial group effects (positive feedback, motivation, cohesion, belongingness, social presence, etc.), the issuer may group the workers into teams. In contrast, to stronger emphasize individualistic aspects, subjects may compete individually.

Although crowdsourcing is very attractive for companies, there is only little research on online crowdsourcing tournaments design itself. A key challenge here is to find an adequate operational mode, incentives, and feedback mechanisms for such tournaments [3, 52].

Tournaments, independent from online and crowd-based scenarios, have previously been analyzed in economic laboratory experiments [10, 18, 19, 59]. Much of the existing literature focuses on
factors directly effective with respect to effort [10, 18, 19, 56, 59]. The role of risk taking behavior in
tournaments and its interplay with feedback (i.e.,
ranking) and grouping (teams or individuals) has
experienced much less attention [45]. Risk taking,
however, may determine a worker’s contribution
quite significantly. On the one hand, high risk taking
may be reflected in workers handing in low-cost-low-
quality work, which does not require much timely or
cognitive effort. Such work of course has a higher
probability of being rejected (and hence not paid) by
the issuer – but this is the risk the worker is willing to
take. On the other hand, especially for tasks
involving creativity, high risk taking may be
desirable as it may result in a variety of more diverse,
offbeat, and extraordinary contributions.

We thus suggest that risk taking in tournaments is
a factor worth considering and that issuers of crowd
tasks may well benefit from better understanding how
different incentive scheme and feedback mechanisms
interact with human risk taking behavior. Risk
propensity may, in this sense, help to unleash the
crowd’s creative potential and to avoid trodden paths
and conformist solutions. For more straightforward
tasks, risk aversion may be the stimulus of choice to
ensure and increase output quality.

In this work, we thus consider how i) tournament
mode (teams or individuals), ii) tournament progress,
and iii) the position in the ranking affect an
individual’s risk taking behavior. Overall, this is
reflected in 3 main research questions:

1. How does the tournament mode (teams or
individuals) affect risk taking behavior?

2. How does tournament progress affect risk taking
behavior?

3. How does the ranking position affect risk taking
behavior?

We address these questions by means of an online
experiment along with the FIFA World Cup 2014.
Participants bet on the outcomes of all 64 matches in
order to earn credit, i.e., we abstract from the factor
effort and hence extract risk taking behavior
specifically.

The remainder of this paper is organized as
follows. Section 2 discusses related work and posits
our experiment in the literature of tournaments.
Section 3 then describes our experimental design. We
present our results in Section 4. Section 5 provides
concluding remarks and sketches out pathways for
future research.

2. Theoretical Background

Crowd-work and online labor markets in
particular (e.g., Amazon Mechanical Turk) have
gained momentum. They offer a mechanism to
distribute work to an open workforce for
comparatively low cost [40, 46]. Today,
crowdsourcing is also used by researchers for
experimental studies utilizing its large subject pool
[46]. Researchers analyzed crowdsourcing regarding
its requirements for research [51], validity and costs
[14], and worker demographics [7, 46]. Besides its
usefulness for research, two of the main challenges
are to incentivize worker effort adequately and thus
secure quality and cost effectiveness [52]. Theories to
assess behavior in these environments must be seen
in front of the background of more fundamental
aspects such as motivation and competition, as well
as their interplay in online.

The intuition to this research can be located in the
streams on cognitive dissonance theory [20, 15],
responsibility diffusion theory [61], and mechanisms
of group conformity [54]. Cognitive dissonance
theory posits that subjects experience conflicting
cognitive states as unpleasant and take actions in
order to resolve or reduce such mental conflict [15].
For the case of rankings, a (positive) self-image is
certainly in conflict with being ranked low, while this
conflict is less likely to occur when being ranked at
or near the top of the list. Behavior with effect on a
subject’s score can hence be expected to be different
for different positions in the ranking. In particular,
cognitive dissonance suggests that falling behind
others alters behavior compared to its “natural” form,
and it does particularly more so than for being on top,
by stressing the importance of catching up. While the
general presence of a tournament mode was found to
result in higher effort levels, rankings often prove to
have a detrimental effect [56, 5]. With respect to risk
taking (chances on high rewards), rankings may be
pointing to a possible path for conflict resolution if
ranked at an unsatisfying position. In may hence be
hypothesized that positions at the bottom of the
ranking entice higher levels of risk taking.

With regard to actions relevant to the entire
group, responsibility diffusion theory states that
individuals feel less responsible for their actions (and
their consequences) in groups compared to acting
individually [21, 55, 63]. Effort in groups was shown
to often suffer due to this diffusion effect [47], also
referred to as “social loafing” [39]. Different levels of
perceived responsibility may also lead to a shift of
risk taking behavior. This can be due to a lack of
motivation to determine the group-optimal risk
strategy, as this may require a lot of effort itself.
Subject may thus take larger risks as they would shine in the light of success but presumably rely on the others in case of failure. In contrast, in groups (compared to individual decisions) there are – after all – others for which subjects may feel responsible and accountable and thus prefer a more moderate, i.e. less risky, behavior.

Moreover, mechanisms of group conformity may entice some team members to adapt the strategies of other members within the group [54], e.g., of those with particular good performance. To the contrary, preferences for individualism may result in choice differentiation [4]. This may result in a plethora of different constellations, depending on which strategies were successful early on. In our study, we rule out this effect by making the group members’ decisions unavailable to others.

In the following subsections, we shed some more light on the factors worker effort, and risk taking in crowdsourcing tournaments by illustrating experimental and empirical evidence on that matter.

2.1. Worker effort

Shaw et al. [52] showed that performance is affected by linking the responses of workers to their peers. Penalizing responses if in conflict with the majority of responses positively influences performance. Mason and Watts [43] reported that higher compensations lead to increased levels of effort, but result quality is not affected. For crowd tournaments (e.g. design contests, open innovation contests, etc.) in particular, effort may be affected by the workers’ risk taking behavior. Many studies in this regard observed high variance in effort [11, 29, 59]. Eriksson et al. [19] demonstrated that self-selection strongly influences effort level and variance. The authors found that average effort was higher and variance was lower when subjects enter the tournament voluntarily. This efficiency-enhancing effect is mainly based on the subjects’ readiness to take risks. Risk averse and underconfident subjects were found to prefer piece rates rather than tournament payoff schemes, where the latter entail higher uncertainty. In contrast to that, motivated, hard-working, and risk-seeking subjects tend to prefer tournaments. As a result, contestant homogeneity is higher when participation is voluntarily chosen, thus leading to a higher average effort with lower variance. Straub et al. [56] analyzed worker heterogeneity in crowdsourcing tournaments.

Particularly, they considered the effects of communicating live rankings (throughout the task), i.e. confronting subjects with the performances of their competitors. Briefly, strong competition was found to make workers quit, while weak competition let workers relax, leading to an overall lower performance with feedback either way.

2.2. Risk in tournaments

Risk taking may be one explanation for high effort variance in tournaments. In order to investigate subjects’ risk taking behavior, it is therefore crucial to better understand the relation between tournaments and rankings. Hvide [34] found that individual risk taking depends on the modification of the tournament: high rewards for the highest performance led to high risks – but not explicitly to hard work. In the domain of sport psychology and motor racing, Bothner et al. [9] considered the impact of positions during races on risk taking. Using data from the NASCAR series, they find that “pressure from below” induces risk taking. “Pressure from above” (the subject sees the opportunity to advance in rank), in contrast, had a smaller impact on risk taking.

As Taylor [57] showed, the gap from sports to corporate decision making is not too large. They examined risk taking behavior in mutual funding competition, in which two fund managers with unequal midyear performances competed against each other for new cash inflows. In short, leading managers avoid risks whereas those behind take risks. The rationale is that losing managers try to catch up. Qiu [49] obtained similar results. Nicken and Sliwka [45] found that risk taking depends on the correlation of the outcomes of risky strategies. In their study, two agents with different scores simultaneously decide between a risky and a safe strategy. The experiment involves different correlations of the outcome of the risky strategy if it is chosen by both. The authors found that the leading player chooses the safe strategy more often whereas the trailing player nearly always plays risky when there is no correlation. However, when the outcome of the risky strategy is perfectly correlated, the leading player chooses the risky strategy more often than the competitor. Bracha and Fershtman [10] found that people rather tend to make risky decisions under tournament conditions than under performance-pay conditions. Subjects make the decisions whether to play a lottery (50:50 chance to win $35 or $10) or to get a guaranteed fixed amount ($22) two times. The first time the decision simply pays the payoffs. The second time the decision is set up as a head-to-head tournament. Only the player with the higher points receives $40, i.e. adding a strategic component. Contrary to the expectation that subjects would choose the safe option more often.
under tournament conditions, the opposite occurred: subjects choose the riskier option more often. Kräkel [38] investigated how risk influences effort and the probability of winning a tournament. While contestants try to minimize their effort, they are willing to take risks when the chance of winning is increased. In uneven tournaments (one or several contestants are more capable to win) the underdogs always prefer risky choices to increase the likelihood of winning. This finding is supported by the results of [6], who examined the risk effect of the contestants’ “spread” in the tournament. Panel data from auto racing showed that drivers take more risks as the spread to the first driver increased. In addition, Grund and Gürtler [28] analyzed the risk taking behavior of professional soccer coaches. Their key finding is that during a match, risk taking of the leading coach decreases with the goal difference. Pull et al. [48] found that in tournaments with high contestant heterogeneity, an increase of the individuals risk will first lead to an enhancement of incentives. After reaching a critical risk level, it will then weaken incentives.

2.3. Risk taking and creativity

Crowdsourcing works well for simple and repetitive tasks. Extending crowdsourcing to creative tasks on a large scale is more difficult to achieve [35]. But creativity is an important factor in several crowdsourcing tasks (e.g. design contests, open innovation contests, etc.). While several crowdsourcing markets exist focusing in creative tasks (e.g. Innocentive, Threadless, 99designs, etc.), it is not clear if they are optimally designed for tapping the workers’ creative potential. Crowdsourcing literature so far focuses on the collaboration of workers to facilitate structures for collaborative creativity processes [35, 62, 44]. Though, it may be beneficial for creative crowdsourcing tasks to incentivize creativity, on an individual as well as on a collaborative level. Literature on creativity suggests that risk taking and intrinsic motivation are the main drivers for creativity [32, 16, 1]. Amabile et al. [1] show in their model that intrinsic motivation is benefitting creative tasks. Compared to offering no reward – intrinsic motivation – offering a reward – extrinsic motivation – decreases creativity. Dewett [16] analyzed the link from intrinsic motivation to creativity in more detail and found that risk taking mediates this relation. Their survey data shows that actually risk taking affects one’s creativity positively. It is therefore vital to induce or reduce participants’ risk taking behavior based on the desired outcome on creativity.

Based on the theory and the empirical insights illustrated in this section, we present the design for an online experiment, systematically investigating the impact of tournament mode (individuals or teams competing), position in the ranking, and tournament progress in Section 3.

3. Experimental Design

The experiment was conducted along with the FIFA World Cup 2014 in June and July 2014, using an online interface. Subjects placed bets on the 64 matches of the tournament and competed for payoffs. A total of 72 subjects participated in the study. Subjects were recruited from a voluntary student pool using Greiner’s Online Recruitment System for Economic Experiments (ORSEE, [26]) at the Karlsruhe Institute of Technology (KIT).

Subjects were assigned either to the team- or the individual treatment, using a between subject design, i.e., in each treatment there were 36 subjects.

Procedure and Task—After an initial online registration on the experiment website, subjects received instructions and user credentials via email. The subjects’ task then was to place bets on the 64 matches over the course of the world cup using the website interface. The bets reflected the possible outcomes for each match – home win, draw, or away win in regular time (3-way-bets). Subjects could discontinue participation at any time during the experiment, like in other online or crowdsourcing tournaments.

Odds were retrieved from the sports bookmaker bwin.com 72 hours prior to match start. The odds reflected the inverse probability of an outcome. More likely outcomes resulted in lower odds. Note that the “true” probabilities of how the matches may end, (e.g., based on a model incorporating all relevant factors) are simply not available – the bookmakers odds are society’s best guess.

Subjects earned points according to the odd if their bet turned out to be correct. Wrong bets resulted in no points. Placing bets was free of charge. Therefore, unlikely events yielded higher potential payoffs (points) than ex ante rather likely events.

Subjects were able to bet on the outcome of a match between 72 hours and 5 minutes before the match started. Betting on all 64 matches was incentivized with an additional payoff of 5€. Forgetting to bet on a specific match resulted in zero points for that match. Figure 1 shows a screenshot of the online interface.
Treatments—Half of the subjects, 36 students, was randomly divided into 6 groups of 6 subjects each. These subjects competed against each other individually within their group (IND). Each subject received points according to the respective odd for each correct bet. After each match, the online ranking was updated (Figure 2). The own position was highlighted (position 1 in Figure 2). After the experiment subjects were paid according to their final individual rank—1st rank 50€; 2nd rank 25€; 3rd rank 15€. Additionally, subjects were able to see an alphabetic list containing their own and the other teams. Please note that this information was not relevant for payoff.

The other half was also randomly divided into 6 groups of 6 subjects each. However, these groups competed as a team against the other teams (TEAM). The individual points of each subject in a team were added up to a team score. After each match the team ranking was updated showing payoff, the total amount of points, average points per subject, and positions of all six teams (Figure 3). The own team position was highlighted (here position 6). Subjects were paid according to their team’s final rank—1st rank 50€ for each team member, 2nd rank 25€ for each team member; 3rd rank 15€ for each team member. In addition, subjects were able to see an alphabetic list showing their own team’s individual performance. Again, please note that this information was not relevant for payoff.

Hence, both treatments were identical—except with respect to the payoff rules. In both treatments, subjects could only see the (assigned) username of the other subjects, whereas communication among subjects was not enabled. The same 6 names were used within all groups/teams.

Before the actual experiment started, subjects were asked to answer comprehension questions by mail in order to ensure proper understanding of the payoff rules and the entire procedure. Four subjects were replaced in response to not answering the questionnaire. After the experiment, subjects conducted questionnaires assessing individual risk aversion [31], competitiveness [27], and the “Big Five” personality traits [50]. Moreover, they were asked to assess their experience during the experiment with regard to perceived social presence [24], perceived competition [12, 60], group belonging [8, 25], arousal [41], and enjoyment [30].

We assess risk taking by the odds that were selected by the subjects. Assuming that the provided odds incorporate all relevant available information, each choice (home, draw, away) has the same expected outcome, but higher odds are more risky than lower odds as they represent a lottery with a higher variance.

Overall 72 subjects (56 male, 16 female) participated in the study. Average age was 21.44 years. All subjects completed the experiment, but not all subjects placed their bets on all games. The challenge of avoiding discontinuation is highly relevant for crowdsourcing. Subjects placed a total of 4,401 (out of 72 × 64 = 4,608) bets, representing a rate of 96%.

4. Results

We now turn to the results of our study. The main focus of our research lies on betting behavior, i.e., which degree of risk subjects are willing to take in their respective treatment condition, with their respective position in the ranking, and tournament progress. As a proxy for risk, we use the selected odd (out of 3) for a given subject and match. Our data thus has a panel structure as we face a timely sequence of 64 decisions (corresponding to the 64
matches) for 72 subjects (with gaps). We hence assess the 3 research questions outlined above by using a GLS regression analysis with subject random effects. Our dependent variable is the selected betting odd.

As independent variables, we use a dummy for the individual treatment (IND), i.e. whether a subject was allocated in the individual or in the team condition. Moreover, to capture tournament progress, we use the number of remaining matches in the tournament (#remaining matches) as temporal panel variable. It states how many open matches there were at the time of placing the bet. This measure is more accurate than using the respective match number since placing bets was allowed within a time frame of 72 hours to 5 minutes before match start, which mostly included several other matches. By using the number of remaining open matches, this variable refers to a fixed state of information at the time of placing the bet. Furthermore, we use the product term IND \times \#remaining matches to capture possible interaction effects between treatment and tournament progress. Furthermore, we use indicators for the position (1 to 6) in both the main ranking (actual relevant for payoff) and the position in the respective other ranking which, however, was irrelevant for the experiment payoffs.

In order to provide some sense for the data and robustness, we present 3 specifications of regression models, building up on each other, in Table 1. Moreover, the relation between tournament progress, treatment, and risk taking (selected odd) is illustrated in Figure 4.

As can be seen in this figure, research question 1 and 2 must be approached in a joint manner, as apparently, tournament mode and progress interact. Whereas overall risk taking increases in the TEAM condition (by .0069 units per match, \(p<.001\)), this increase is even higher in the IND condition (.069 + 0.039 = .0108 per match, \(p<.05\)). Starting from a negligible difference at the beginning of the tournament, this treatment difference amounts to (marginally significant) .2432 units towards the end. We conclude that subjects increase their risk taking behavior over the course of the tournament, where this increase is significantly more pronounced in the IND condition.

Second, with regard to position in the ranking, the results are a little less obvious. While the actual relevant payoff in model b) does not show to have any effect, including the irrelevant ranking position in model c) changes the picture: positions at the bottom of the ranking are associated with less risk taking. This observation is persistent in direction and magnitude with regard to removing the relevant rank variable and also to adding other control variables for ranking position (e.g., position in the \textit{IND} or \textit{TEAM} ranking). Controlling for gender and risk aversion did not reveal any significant effect or model improvement.

<table>
<thead>
<tr>
<th>Table 1. Mixed effects regression—dep. variable: risk taking (selected odd).</th>
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<td>a) &amp; b) &amp; c)</td>
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<tr>
<td>\textbf{treatment: IND} &amp; (\hat{b} = .243) &amp; (\hat{b} = .244) &amp; (\hat{b} = .241)</td>
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<td>&amp; (.127) &amp; (.124) &amp; (.124)</td>
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<td>#remaining matches &amp; (\hat{b} = -.007) *** &amp; (\hat{b} = -.007) *** &amp; (\hat{b} = -.007) ***</td>
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<td>&amp; (.001) &amp; (.001) &amp; (.001)</td>
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<tr>
<td>\textit{IND} \times #remaining matches &amp; (\hat{b} = -.004) * &amp; (\hat{b} = -.004) * &amp; (\hat{b} = -.004) *</td>
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<td>&amp; (.002) &amp; (.002) &amp; (.002)</td>
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<td>rank (relevant) &amp; (\hat{b} = .003) &amp; (\hat{b} = .010)</td>
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<td>&amp; (.014) &amp; (.014)</td>
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<td>rank (irrelevant) &amp; &amp; (\hat{b} = -.031)</td>
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<td>&amp; &amp; (.013)</td>
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<td>constant &amp; (\hat{b} = 2.641) *** &amp; (\hat{b} = 2.629) *** &amp; (\hat{b} = 2.727) ***</td>
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<td>&amp; (.090) &amp; (.103) &amp; (.111)</td>
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Dependent variable: risk taking (selected odd); Standard errors in parentheses. Significance codes: ‘

\textit{****}’ \(p<.001\); ‘

\textit{***}’ \(p<.01\); ‘

\textit{**}’ \(p<.05\); ‘

\textit{*}’ \(p<.1\).}

\(\hat{b}\) represents the regression coefficients, and \(\hat{b}\) represents the estimated average treatment effect. The regression models are computed using GLS regression analysis with subject random effects. The dependent variable is the selected betting odd, and the independent variables include a dummy for the individual treatment (IND), the number of remaining matches, the interaction between IND and the number of remaining matches, and indicators for the position in the ranking. The results are presented in Table 1, which includes the regression estimates, standard errors, and significance levels. The model specifications are as follows:

- **a)** Treatment: IND
- **b)** Treatment: IND + #remaining matches
- **c)** Treatment: IND + #remaining matches + IND \times #remaining matches

The table shows the estimated coefficients for each model specification, along with the standard errors in parentheses. The significance codes are indicated as follows:

- ‘\textit{****}’ for \(p<.001\)
- ‘\textit{***}’ for \(p<.01\)
- ‘\textit{**}’ for \(p<.05\)
- ‘\textit{*}’ for \(p<.1\)

The model specifications are set up to capture the interaction between treatment and tournament progress, as well as the effect of remaining matches on risk taking.

In Figure 4, the comparison of risk (selected odd) by individual and team ranking over the course of the tournament (GLS regression estimates) is illustrated. The trends show an increase in risk taking over time, with IND subjects showing a more pronounced increase compared to TEAM subjects. The figure highlights the joint approach to research questions 1 and 2, indicating that tournament mode and progress interact significantly.
5. Discussion, Limitations, Future Work

In this paper we presented results of an experiment, analyzing the interplay of individual and group rankings with risk taking behavior. Our results indicate that risk taking increases over the course of a tournament and that this increase is stronger for individual (compared to team) rankings. The ranking position itself exhibits an unexpected effect: whereas the payoff relevant position does not appear to impact risk taking, the complementary ranking does, decreasing risk taking for worse positions.

This paper contributes to the discussion on how to design crowdsourcing tournaments online. Our results indicate that assessing crowdsourcing in tournaments should be assessed carefully with regard to risk taking. Fundamental design variables like payoff rules and feedback information were found to impact risk taking behavior. Besides higher levels of effort and variance [11, 29, 59], an issuer of a crowd task may hence also deliberately control risk taking behavior. This might be especially helpful for tasks requiring high levels of creativity such as design and innovation contests. Adequate payoff and feedback schemes then help to tap the workers’ creative potential by inducing, encouraging, and emphasizing risk taking behavior.

With regard to the shift in risk taking behavior over time, Effrey et al. [17], for instance, found that participants in a self-reported coin-flip experiment tended to cheat on their last (expected) trials, represented by statistically unnatural high fractions of paying coin flips, which the authors related to the subjects’ anticipated regret over missing the (last) chance to enrich themselves. For the case of betting, cheating can be ruled out as an issue as there is simply no way to cheat. We suggest that the increase in risk taking towards the end rather stems from the increasing awareness that only so many matches remain to have a substantial lucky hit and hence to advance in the ranking, comparable to long-shot bets at the end of the day in horse races [13]. This is in line with the finding that this increase in risk taking is more pronounced for individuals than for teams, as the impact of such a bet is potentially mitigated by the other group members’ behaviors.

For platform operators, this means that creating long-shot situations may be a suitable way to induce risk taking behaviors and – implicitly linked to this – unleash silent creative potentials. Note that we do not claim that individually increasing subjects’ creativity is possible, as creativity was often found to be inhibited by extrinsic motivators [1]. Rather we suggest creating a platform environment which encourages creative subjects to actually pursue their “wild” ideas and not to hand in mainstream – and hence presumably more “secure” – draftings.

Several limitations of this study are obvious. Since the World Cup is associated with a lot of emotion to many viewers, so might be the participants’ betting and hence risk taking behavior. Preferences for certain teams might have distorted behavior. Controlling for the participants’ favorite team did not reveal interference with risk taking. Preferring a second over a third team might have still had an influence, which we cannot account for.

Another issue stems from the fact that we used odds from www.bwin.com 72 hours before the match started. Of course, odds may have changed until 5 minutes before the start of the match, which we believe was no mystery to subjects. Differences here could have been used for arbitrage betting.

Even though our study represents a rather natural online experiment, it does not consider an actual crowd working task or platform. As implementation issues are often the greatest challenge for crowdsourcing systems, future work should thus take research on risk taking behavior in crowd work to natural field experiments in this domain. Similar approaches without taking risk into account are provided by [42, 53]. To conclude, crowd work has experienced rapid growth and can be expected to do so in the future, not only as a means of outsourcing, but also as complementary base of intelligence for machine learning systems. The underlying level of risk taking may be valuable information and even a set screw for task quality.

References


