Abstract

Crowdsourcing has become a prominent means for idea generation in NPD. Often firms rely on the help of crowdsourcing platforms who act as intermediaries that connect, translate, and facilitate the flow of knowledge between seekers and solvers. Among the various established crowdsourcing intermediaries in current use, the competition-based model can be seen as the prevailing model. Existing research, however, offers limited insights on how the social interaction within the platform may affect participation engagement within the platform. Especially forms and effect of negative interaction between members of crowdsourcing communities have remained little investigated. We address this void and investigate the social interactions between members of competition-based crowdsourcing communities using data from a large European idea crowdsourcing platform. We analyze empirically the impact of social interaction between members on two dimensions: the idea success of the recipient, as well as participation behavior. We differ between likes, positive and negative effects and measure the specific effects related to the member category of the ?sender? and ?recipient?. The results indicate that likes and positive comments increase the success probability of an idea. Negative comments, however, show a negative effect only when the sender belongs to the top-innovator group. Interestingly, we do not find any negative effects on participation behavior of the receivers. Instead, all types of social interaction increase the participation behavior in the short run (one week ahead). Our results provide implications for managers of crowdsourcing platforms.
ABSTRACT

Crowdsourcing has become a prominent means for idea generation in NPD. Often firms rely on the help of crowdsourcing platforms who act as intermediaries that connect, translate, and facilitate the flow of knowledge between seekers and solvers. Among the various established crowdsourcing intermediaries in current use, the competition-based model can be seen as the prevailing model. Existing research, however, offers limited insights on how the social interaction within the platform may affect participation engagement within the platform. Especially forms and effect of negative interaction between members of crowdsourcing communities have remained little investigated. We address this void and investigate the social interactions between members of competition-based crowdsourcing communities using data from a large European idea crowdsourcing platform. We analyze empirically the impact of social interaction between members on two dimensions: the idea success of the recipient, as well as participation behavior. We differ between likes, positive and negative effects and measure the specific effects related to the member category of the “sender” and “recipient”. The results indicate that likes and positive comments increase the success probability of an idea. Negative comments, however, show a negative effect only when the sender belongs to the top-innovator group. Interestingly, we do not find any negative effects on participation behavior of the receivers. Instead, all types of social interaction increase the participation behavior in the short run (one week ahead). Our results provide implications for managers of crowdsourcing platforms.
INTRODUCTION

The inclusion of external ideas for new product development has become an imperative and standard for many companies. One popular way of gathering new product ideas externally, are crowdsourcing platforms. Crowdsourcing platforms provide an alternative channel to broadcast problems to a large, undefined unknown group of people, in the expectation of receiving back creative solutions and innovative ideas with potentially high commercial attractiveness (Kelley & Littman, 2006; Howe, 2006; Brabham, 2010). In recent years, we saw the emergence of prominent ventures that capture value by building their business model around crowdsourcing for new product development (Kohler, 2015). Threadless for example has a crowd of some hundred thousand people who design the motives for their T-Shirts. Top-Coder unifies a crowd of highly skilled software programmers who write customized software solutions to clients approaching the platform (Lakhani, Garvin, & Lonstein, 2010), and Innocentive makes use of the specialist knowledge of its crowd members in many different areas.

The process of idea generation within crowdsourcing platforms is either performed collaboratively through peer-production, or individually by participants working alone (Afuah & Tucci, 2012; Howe, 2006). Frequently crowdsourcing platforms make use of idea contests in which members of the crowd involved compete to win monetary rewards for delivering the contest winning solutions (King & Lakhani, 2013). Idea competitions may be defined as an invitation made by a private or public organizer (seeker) to the general public or a targeted group (crowd) to submit solutions to a challenge within a certain allowed time period (Bullinger, Neyer, Rass, & Moeslein, 2010; Ebner, Leimeister, & Krcmar, 2009). Most of the established crowdsourcing intermediaries make use of the competition-based model for setting up the crowdsourcing process (Colombo, Buganza, Klanner, & Roiser, 2013).

The benefits for the problem-broadcasting companies are evident because they get access to a wide variety of skills and creativity and thereby extend the space of available solutions (Malone, Laubacher & Dellarocca 2010). Often, through crowdsourcing, companies can solve problems that they have been working on internally for years (Boudreau, Lacetera, & Lakhani, 2011). They get better solutions, in shorter time and at lower costs compared to permanently employed internal staff. However, platform owners face the challenge of integrating and managing a crowd consisting of thousands of independent individuals.

More recent work has focused on the dark side of crowdsourcing has been discussed. Especially the fairness aspect towards the crowd (in terms of distributive and procedural fairness) has received some attention (e.g. Franke et al. 2013, Faullant et al. 2017), showing that unfair conditions may prevent users upfront to participate in idea competitions, or limiting the potential of positive customer relationship-related consequences for the hosting firm. Some voices appeared criticizing crowdsourcing-based business models for exploitation and “producing too much social waste” (Di Fiore, Van Alstyne, & Schneider, 2017). Because most crowdsourcing-based business models apply competition-based systems, usually there are only few winners. With a limited number of winning ideas to be awarded and several hundreds or even thousands of submissions, the chances to win a prize as a crowd member become sometime less than 5%, sometimes also below 1%. In the long run, this skewed winner distribution may undermine the crowd community, limit the
willingness of members to participate in future and thereby threaten the business model of the platform provider.

Consequently, the low winning chances by nature increase the rivalry among participants and ultimately may also generate malicious behavior among participants. A recent study by Faullant & Dolfus (2017) showed that social interactions among members of the crowd partly have strikingly destructive character and that there is fierce competition among solvers aiming for being prominently listed in the list of Top-Innovators of a community. Since this study is based on qualitative interviews one cannot conclude whether sabotage in competition-based crowdsourcing communities is a large or a minor phenomenon and what the consequences are. Tournament literature, however, suggests that crowdsourcing competitions resemble in many aspects those situations where sabotage is a frequently observed phenomenon. We claim that the literature on crowdsourcing-based new product development so far has mainly focused on users’ motivation to engage (for a review see Ghezzi et al. 2017) and draws an overly positive picture of an intrinsically motivated crowd helping each other. We know little about malicious behavior among community members and their possible impact on other solvers and their future activities. Therefore, the main research questions of this paper are:

a) How frequent is the phenomenon of sabotage in the social interactions among members of competition-based crowdsourcing communities?

b) What is the impact of sabotage on the recipient members’ idea success and participation behavior?

To answer these questions, we build on tournament literature and we show that this kind of setting resembles in many aspects that of tournaments where sabotage is a commonly observed behavior. We then analyze these effects empirically, using data from a large European idea crowdsourcing platform and the interaction patterns among its participants. Our results provide implications providers of crowdsourcing campaigns.

THEORETICAL BACKGROUND AND RELATED WORK

**Competition-based crowdsourcing for idea generation**

Crowdsourcing can be applied for various problems and in multiple forms. In general, crowdsourcing strives for solving problems in various directions using a crowd as potential solvers. In order to obtain high quality solutions, seekers provide appropriate (monetary) incentives to those members providing the best solutions (Gao, Bachrach, Key & Graepel, 2012). As such, crowdsourcing aims at stimulating both the quantity and the quality of possible solutions (Afuah & Tucci 2012).

Crowdsourcing for idea generation in new product development has become particularly popular and is seen as one of the most promising forms of open innovation (Chawla, Hartline & Sivan, 2012). Though crowdsourcing tasks for new product development can be performed also collaboratively, the predominant model is a competition-based model, where individual participants compete with their solutions for the prizes advertised. As such they are a digital renaissance of an old concept that has been in place for problem solving since centuries, i.e. idea competitions. Due to the pace of development of internet
technologies, crowdsourcing-based idea competitions recently gained remarkable popularity on the web (Zhao & Zhu, 2014). There are a number of different concepts of idea competitions that finally follow the process of transferring innovative ideas from a crowd to the seeking company (Geiger, Seedorf, Schulze, Nickerson & Schader, 2011). Companies via company owned platforms, addressing competitions to an internal or external crowd, can directly launch idea competitions. Alternatively, firms can also opt for posting their problems on problem broadcasting platforms (provided by intermediaries) with an existing crowd, where contests can be accessible by the entire crowd or restricted to a subset of the crowd whenever a restriction in terms of participating members is needed. Platforms act as intermediaries between seekers and solvers. Seeking companies can easily publish their problems to individuals with diverse expertise all over the world in the expectation of receiving creative solutions to their problems (Terwiesch & Xu, 2008).

![FIGURE 1 Choice of idea competition](image)

**Communities and Competition**

In contrast to their ancient predecessors, participants of crowdsourcing-based idea competitions nowadays do not operate in isolation. Crowdsourcing initiatives are usually set-up as web-based interactive idea platforms allowing for rich social interaction among participants (Estellés-Arolas & González-Ladrón-de-Guevara, 2012). The platform’s technical set-up is seen as critical as it may significantly enhance participants' contributions on crowdsourcing platforms (Leimeister, Huber, Bretschneider, & Krcmar, 2009). Depending on the design, crowdsourcing platforms can provoke and promote intense interaction among participants not only allowing them to disclose their ideas to the initiator, but also to make suggestions for improvements to other participants’ work, to vote for their favorite idea or design, and discuss various topics by posting comments. Through these interactions a sense of community can emerge where participants support and help each other. On the other hand however, they are all competing for the very limited prizes (Faullant & Dolfus 2017). For participants being part of a crowdsourcing contest, “community” is associated with both experiencing a sense of collectively achieving a target, but at the same time being competitors trying to provide a compelling solution to the organization to win a prize (Hutter, Hautz, Füller, Mueller, & Matzler, 2011). Some studies have already shown that there exist differences between participants in their collaboration orientation: some seem to comment and interact more than others, while
some prefer not to comment at all or make their submission rather towards the end of the contest (Bullinger, Neyer, Rass, & Moeslein, 2010). Also the set-up of the contest itself can influence the collaboration behavior: idea communities lacking the competitive element of a prize to win generate much more comments and interactions than competition-based crowdsourcing communities (Bretschneider et al. 2012). In innovation communities lacking competitive elements participants also develop psychological ownership of the knowledge jointly produced by the innovation community and consequently tend to greater knowledge sharing (Pirkkalainen 2018). Finally, some studies have investigated how the personality dispositions influence participation behavior, and found that participants in idea competitions score higher on trait competitiveness (Faullant et al. 2016), and that participants with higher scores in machiavellism characteristics are more prone to show anti-social behavior on such platforms (Hutter et al. 2015). The competitive element of crowdsourcing competitions obviously has some impact on participants’ behavior, which in some cases may result in malicious actions like negative comments, negative likes, copying of ideas or even verbal battles as outlined in the recent study by Faullant and Dolfus (2017). Their impact on the recipients however is unclear. Do they try harder? Do they give up? And what are the consequences for the submitted ideas?

Since malicious behavior and sabotage are a frequently observed behavior in all kind of situations of rank order we next give an overview of the fundamentals of tournament theory which serves as an appropriate theoretical background.

**Linking tournament literature to crowdsourcing competitions**

Tournaments are contests where participants compete for prizes that are set before and awarded based on the rank order at the finish, not the absolute performance of each contestant (Becker & Husedit 1992). Tournament theory originally was developed in the economic labor research and aims to explain larger pay differences in wages as for example between CEOs and workers (Lazear & Rosen, 1981). The theory posits that compensation schemes in form of relative rank order under certain conditions is superior to absolute pay-for-performance schemes. Whereas in pay-for-performance schemes the absolute value of the work is judged and rewarded, in tournaments it is the relative performance of each contestant in comparison to the other participants of the tournament. Therefore, in tournaments marginal performance increases can lead to a large difference in payouts (Connelly et al. 2014). Tournaments are especially effective in situations where absolute performance in terms of exerted effort is difficult or very costly to monitor or to judge. In such situations, it is easier to relate payments to more easy observable output-levels and compare the relative performance (Lazear & Rosen, 1981). Rank-order prizes are therefore seen as a way to motivate a broader base of employees who strive for promotion. Research on tournaments has gained much attention in the management literature to explain compensation structures and to determine the optimal prize structure Connelly et al. 2014).

Also for innovation and idea contests tournaments have been described as an appropriate means. The generation of ideas and innovative solutions, much like job performance, is difficult to monitor. Most times the value of an idea or solution cannot be judged immediately or before full realization. Therefore, tournaments seem to be an adequate frame to look at innovation contests. Morgan and Wang (2010) outline why and when idea contests are recommended and provide decision trees for the optimal design of idea
tournaments. In the context of innovation contexts Terwiesch and Xu (2009) and Boudreau et al. (2011) show that the problem of solvers’ underinvestment through a larger pool of participants can be outweighed by the diversity benefits received from an increased number of contestants.

An important stream of literature related to tournament research is that of sabotage in tournaments. Research from this stream of literature indicates that sabotage in tournaments is a frequent form of players in order to improve the own winning chances (Harbring & Irlenbusch, 2008). The problem of sabotage in tournaments results from the fact that peers can choose between (at least) two dimensions of activities in order to improve their relative position - they can, alternatively to intensifying their own productive effort, also deteriorate their competitors’ performance by means of destructive activities (Harbring & Irlenbusch, 2005). The problem of destructive behavior increases as the wage spread becomes larger (Harbring & Irlenbusch, 2011), and research has shown that especially capable members in promotion tournaments are more often the victims of sabotage (Chen, 2003). Overall sabotage is destructive as it not only destroys resources, but also severely depresses incentives to work productively and daunts motivated participants (Gürtler & Münster, 2010).

Scholars have furthermore investigated the influence of intermediate information and found that information on the rank additionally increases sabotage, thus when contestants find out that they lag behind (but the race is still not lost) they engage in more sabotage activities (Deutscher and Schneemann, 2017). Sabotage was not only studied for monetary incentives, but also for recognition and status. The effects have been the same: in non-pecuniary recognition programs based on relative performance participants increased both their own efforts but also their counterproductive efforts in decreasing their peers’ performance (Wang, 2017). The effect of intermediate information has also been identified in the context of competitions for status, where feedback on the ranking of the candidates increases the likelihood of sabotage (Charness, Masclet, & Villeval, 2014).

Transferring these findings to the crowdsourcing contest with competitive character, we state that most crowdsourcing platforms actually provide very similar conditions as in promotion tournaments: most platforms organize competition-based challenges, they make use of rankings and Top-innovator lists, and they enable channels for direct interaction with peers. The findings on sabotage in non-pecuniary settings underline the relevance for crowdsourcing idea contests, because many participants besides aiming to win the prize indicate a strong participation motivation by semi-extrinsic factors such as recognition by peers, or expert ranking in the community. The findings on intermediate information increasing sabotage is relevant for the context of ideas contests too, because online idea platforms allow for immediate performance feedback in terms of likes and comments received. In crowdsourcing and innovation contest literature however sabotage as a potentially destructive behavior has largely been neglected. Naroditskiy et al. (2014) in a formal model show that especially in contests with open-access (i.e. no entry barriers) sabotage could be rather the norm than the exception. They claim that many successful examples of crowdsourcing may have been overshadowed by unexpected incidents where sabotage destroyed or severely hindered collective efforts. As such, crowdsourcing may actually result in a dilemma: despite crowdsourcing being a more efficient way of accomplishing multiple tasks, crowdsourcing is also a less secure approach in a competitive environment where there is a natural desire to hurt the opponent. Malicious behavior in
crowdsourcing competitions can result in (e.g.) personal attacks and individual sabotage. The various channels of social interaction such as making comments, casting votes or making evaluations might be a double-edged sword, supporting those who receive positive feedback that enhances their feeling of competence and autonomy, while discouraging those who receive no attention or negative feedback.

Since sabotage in crowdsourcing idea contests has not yet been proven quantitatively we investigate this in a real-life setting. Our empirical longitudinal data from a major crowdsourcing platform allows us to identify various forms of sabotage and their potential impact on successive performance of the competitors. Additionally, we also investigate the impact of positive interactions such as likes and comments.

EMPIRICAL STUDY

The crowdsourcing platform

The crowdsourcing intermediary being analyzed is one of the major crowdsourcing platforms in Europe. More than 380 crowdsourcing competitions have been successfully launched and executed since the platform's go-live in early 2007. Within the registered solvers nearly 26,000 active innovators compete for awards and price-money. Until today, more than EUR 600,000 prize-money has been awarded to the crowd. The crowdsourcing platform acts as an intermediary between seeking companies and members of the crowd. In that role, the platform allows companies to include the crowd in solving company-specific problems by inviting the community to submit solutions to a challenge with the aim of generating proper ideas.

Within the platforms’ standard idea competition process seekers (usually a company) initially formulate a task description containing guidelines and requirements (criteria to narrow down either the topic or the range of ideas given) for further submissions including the monetary rewards. Furthermore, information about accepted languages for ideas, comments related to the competition, and the duration of the competition (usually 1 to 2 months) are announced. Additionally, a project contains information about the status of the competition: ongoing, in evaluation, or closed. Each competition has a moderator, usually an employee of the company owning the competition. The crowdsourcing platform (as well as the competitions announced) is set-up in a way that social interaction is actively promoted and supported by the intermediary. The platform offers diverse forms of interaction so that the community is able to both communicate with seekers as well as other solvers using different channels.

The platform uses an incentive scheme that is based on monetary as well as non-pecuniary benefits for the participants. In each contest, a prize is set out (approx. €1,000) which is distributed among the winning ideas. The sponsoring company determines at the end of the contest how many ideas it wishes to award, the prize for the winner therefore is not fixed upfront. A very important non-pecuniary incentive for members of the crowd is provided by the ranking in the top innovator lists, published by the platform. The ranking of ideators in various lists is based on a system of collecting "points" for any action and interaction of users. The three different types of "Top Innovators" lists are as follows:

- Activity and Endurance: a contestant's total number of points collected over the entire duration of membership of the community;
Quality and Efficiency: the ratio between the total number of ideas submitted by a contestant and the number of award-winning ideas; and

Climber of the week: contestants’ number of points collected during the last 7 days.

Each single list prominently highlights the 20 Top Innovators in the respective category. The lists are prominently placed on the webpage of the platform, visible for all visitors. Occupying a Top-20 rank is associated not only with higher standing in the community but predominantly also with the probability of future job opportunities at the broadcasting firms in addition to winning a competition. Crowdsourcing platforms commonly use such lists when seeking to motivate their members to contribute constantly (Schenk and Guittard, 2011). Contributors climb up the lists by collecting points for their interactions. Points can be collected both being active oneself (e.g. by posting ideas and comments) and by passively receiving comments and likes to own ideas from others.

### Demographics of the crowd

Demographic information for the sample of users includes age, gender, location, employment status and profession. The platform analyzed being one of the major European crowdsourcing intermediaries built up an active crowd with nearly 26,000 active members (at least one idea submitted) spread across multiple countries: 90% of users are from predominantly German speaking countries, 4% of users in the US, and 1% each in China, France and India. 71% of solvers are male, 29% female. As far as the age of solvers is concerned the crowd is structured as follows: 1% of the crowd is younger than 20 years, 20% is between 20 and 30 years old, 35% between 30 and 40, 25% between 40 and 50, 20% is older than 50 years. With different levels of education members of the crowd are diversified with the following employment status: 37% employees, 19% students, 15% executives, 14% entrepreneurs, 11% freelancers, 2% unemployed, 2% retired.

### Member activity

All interaction of solvers as well as seekers is logged in a server-side relational database. Recorded variables are available as semi-structured data dump (csv) allowing research on social interaction. Activity data associated with social interaction is reflected for all users who had participated at least once in a competition; those who had registered on the platform but had never contributed are excluded. The platforms' taxonomy requires members to provide their real names. For the analysis, we exclude all identifiable information and cases with system generated errors. Additionally, we have the rank information of each participant in the prominent top innovator activity and endurance list, and retrieved three subsets of participants: Top 20 users, Rising Stars (users with rank 21-50) and contributors outside the list of Top 50 innovators (see section on activity index for a description of the user categorization). Each interaction then (e.g. likes sent/received, ideas published or comments given/received) is linked to the user’s category (Top 20 users, rising stars, outsiders). This detailing of data allows us to consider also the relative rank of each member to a certain date, and allows us to make a more profound analysis on whether the current position of a member is related to potential sabotage behavior.

The ranking of users in the list of top innovators is driven by a scheme of gathering "points" for various action and interactions - the more points gathered, the higher the contestant's ranking in the various lists. Points can be collected by being active oneself (e.g.
by posting ideas and comments), but also passively by receiving for example comments and likes from others. The users themselves may directly regulate active communication, whereas it is others (other users or the moderator) who always determine the amount of the passive communication an individual user receives. Two thirds of points gathered by Top-20 users as well as by Rising Stars have been collected in active ways, which indicates a high level of active presence on the platform by these users. Figure 2 displays the curves of cumulated points collected by Top20 users and by Rising Stars.

![Figure 2: Cumulated points collected 1.1.2013 – 31.12.2013](image)

For our further empirical analyses, we use data from 2013. In 2013 121 idea competitions were launched on the platform with in total 34,280 ideas submitted. Out of a total of 34,280 ideas, 49.8% were submitted from outsiders, followed by 31.6% from Top20 members, and 18.6% from rising stars. On average, thus, each competition generated 167.7 ideas (min=1, max= 602). The number of winners ranges between 2 and 56. For each project and each idea, we have information on whether it was a winning idea or not, on the group membership of the author, as well as on the activity that it generated in the platform. Specifically, we have information on the number of likes, and comments give to each idea by other members. On average, ideas received .6 comments (min=0, max=29) and 3.6 likes (min=0, max=32).

**Network analysis of sabotage behavior**

Descriptive statistics indicate that there may be sabotage activity initiated by the Top20 users. All comments given to ideas raised in 2013 have been categorized as follows: neutral comment, comment for improvement, positive comment, negative comment, personal attack, reference that idea is a copy. Given the fact that comments are published in various languages, in different contexts and often as part of a connected conversation, any natural language processing was not helping for proper evaluation. To get the best rating possible each of the 20,152 comments has been interpreted and rated by two independent raters. The analysis of rated comments shows that 1% of all comments posted in 2013 were personal attacks and additional 5% of comments were negatively flavored. Unexpectedly, only 15% of the entire comments were of positive content whereas 22% of all comments are categorized as suggestions for improvement for others’ ideas. 35% of all
personal attacks by commenting ideas were posted by only 6 Top-20 users and additional 11% were given by only two Rising Stars. The figures show that there are personal attacks going on, but only a few users are responsible for this destructive behavior.

We visualize the network of personal attacks and negative comments (see Figures 3, panels a and b). In both panels we visualize the core network and display group membership by color (red represents Top20, blue represents Rising Stars and grey represents Outsiders). The node size indicates the centrality degree of a member in the network, whereas the tie strength represents the number of interactions (attacks or negative comments). Both networks show that Top20 members have a central place, and that they attack other groups, but also each-other. This indicates clearly that Top20 members have a central role in initiating negative activities within the platform. We aim to measure the effects of this negative activity on two outcomes: winning probability of an idea and future engagement of receivers of these attacks.

![Core network of personal attacks](image1.png)

![Core network of negative comments](image2.png)

FIGURE 3: Network analysis of personal attacks and negative comments

RESULTS

General approach

We analyze the effect of the members’ activity and reactions on two different levels. First, we investigate how the generated activity of an idea (comment or like) affects the winning probability of this idea. For this, we conduct an analysis at the idea level. Secondly, we examine on a user level how the reactions by other users affect the future engagement within the platform. For this, we conduct analysis at the user level. Both these indicators, winning probability of an idea, and user engagement within the platform are highly relevant for the platform management. In addition, by quantifying the effects on these two levels, we generate new insights on effects of user engagement and user interaction in crowdsourcing platforms.

Effects of user engagement on winning probability of ideas

The units of analysis are ideas, i.e., we analyze on an idea level the impact of likes and comments on its winning probability. We differentiate the givers of likes and comments according to the three user groups outlined above. This means that we know the number of likes and comments from Top20, Rising Stars and Outsiders. We go a step further and
categorize comments based on their valence into positive and negative comments. For likes, positive and negative comments, we are able to measure the number from each member group. We conduct a stepwise analysis. In all models, we use the information whether an idea won or not (1 = yes/0 = no). The focal variables are likes and comments, but the degree of specification differs between the models. In Model 1 we analyze the influence of the total likes and comments, independently of the author. In Model 2 we measure the influence of positive and negative comments separately. Model 3 differentiates comments not only with respect to their valence, but also regarding the author ranking. Last, in Model 4 we include interaction effects between the idea authors and the likes/comment authors to investigate engagement dynamics between these groups. In all models we control for the group membership of the idea author, the total number of proposed ideas by an author in 2013, as well as for seasonality by including fixed effects for month of the year. We also account for unobserved heterogeneity at a project level, which is not captured by the controls in our model by including a random intercept.

The results show that, as expected, ideas that generate more traffic are more likely to win. Both, likes \( (b = .73, \text{se} = .05, p = .00) \) and comments matter \( (b = .28, \text{se} = .05, p = .00) \), although the effect of likes is higher, given that comments measure only the traffic intensity, but not the valence, i.e., we do not differentiate between positive and negative comments in Model 1. We do this in Model 2 and see that while more positive comments increase the likelihood of an idea to win \( (b = .60, \text{se} = .07, p = .00) \), there is no negative effect from the negative comments \( (b = -.04, \text{se} = .12, p = .76) \).

To understand these effects better, we measure the number of likes, positive and negative comments for each member group. For likes and positive comments, the positive effect on the likelihood of an idea to win emerges for all member groups. For negative comments, we only find a negative effect of the comments coming from Top20 members \( (b = -.46, \text{se} = .24, p = .06) \). This finding suggests that the opinion of the Top20 members is important for winning decisions of ideas. Last, in Model 4 we build interactions between the author of an idea and the number of positive and negative comments from the different member groups (Outsiders are the baseline). We find significant interaction effects (see Model 4 in Table 1). Specifically, more positive comments from Top20 members to ideas suggested by Rising Star authors, and more positive comments from Top20 members to Top20 authors increase the winning probability of an idea. Interestingly, we also find positive effects emerging from negative comments: more negative comments by outsiders to ideas by Rising Stars, as well as the more negative comments by Rising Stars to Top20 ideas increase the probability to win. Keeping in mind that Outsider members are the baseline, these positive effects suggest that negative effects hurt less for ideas suggested by other member groups.
Table 1: Effects of member activity on winning probability of ideas

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Note: Month dummies were part of the model but are not displayed to save space. RS=Rising Star. Baseline are Outsider authors.
Next, we investigate how received likes and comments affect the activity level of platform members. For this, we analyze data at the individual member level. We have the weekly given and received number of likes, positive and negative comments. We estimate Tobit Type 1 models with 0 as lower limit, and include member specific random intercepts to account for unobserved heterogeneity. We specify Models 5 – 10 which differ regarding the dependent variable (Models 5 and 7 use likes as dependent variable, Models 6 and 8 the total number of comments and Models 9 and 10 the number of positive and negative comments, respectively (see Table 2). All dependent variables are lagged by one week, i.e., we look at member participation in week t+1 due to received likes or comments in week t.

We see in Models 5 and 6 that more received likes and comments result into more given likes (Model 5) and comments (Model 6). Model 7 shows that the number of likes is significantly driven by positive comments given by Outsiders and Top20 members. Interestingly, the negative comments by Top20 members also lead to higher number of given likes. Model 8 reveals that the number of given comments is affected positively by all types of activities, independently of author group. Looking at positive and negative given comments separately, we see that this positive effect of all types of activities is consistent for both types of comments.

To summarize, we see that received traffic, likes, positive or negative comments, increase the traffic and the activity of platform members. This might seem somewhat counterintuitive at the first impression, however, looking into some of the negative comments, we see that most comments, independently of their valence trigger a response – being it a “Thanks for the good suggestion” or a reply to the negative comment. Therefore this finding seems plausible.
Table 2: Effects of member engagement on member activity

<table>
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<th>Model 5: Liking</th>
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<th>Model 7: Likes</th>
<th>Model 8: Comments</th>
<th>Model 9: Positive comments</th>
<th>Model 10: Negative comments</th>
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29748.00  
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21641.84  

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DISCUSSION

Crowdsourcing competitions have become one of the most capable tools for user co-creation in the context of open innovation. Numerous examples proved the power of crowdsourcing to solve problems of different nature of difficulty. However, the positive examples can be overshadowed malicious behaviour among the members of crowdsourcing competitions. To our best knowledge with our study we are the first to provide quantitative empirical evidence on sabotage behavior in crowdsourcing-based idea competitions and the consequences on the recipient’s chances to win and the further activity on the platform itself. Our analysis shows, social interactions in crowdsourcing-based idea competitions are – besides of their collaborative nature – also characterized by destructive behavior. The sabotage behavior largely results from the tough competition between those members who struggle for a Top-20 ranking. The competitive climate within the community seems to be a major reason for solvers trying harder climbing up the prominent lists of Top-innovators. Apparently, various solvers make use of all the channels of social interaction provided by the platform to both rising up the lists and to prevent themselves from getting relegated. Our descriptive results of the network analysis show that the Top20 members of the community are heavily involved in negative behaviors, such as personal attacks and negative comments to others. This is a finding that stands in some contrast to literature on sabotage in tournaments which posits that especially capable participants are often the victims of sabotage (Chen et al. 2003). Our results rather support the picture of a strong rivalry within the group of highest-ranking members but also outgoing negative activity towards members of other groups. As a possible explanation, we assume that Top20 contributors try to defend their ranking position regarding all means as justified.

The next critical question than is, does sabotage hurt the recipient? To this question we investigated the impact of all kinds of interactions on 1) the members’ activity and 2) on the recipient idea’s winning chances and we presented mixed findings. A first general finding is, the more traffic an idea raises the higher are its winning chances, for eventual negative comments received, only those coming from Top20 users decrease the winning chances. On the other hand, positive comments from Top20 members also increase the winning chances for other Top20 and Raising Star users. Top20 users are therefore considered as especially influential. A similar finding on the influence of a few over many others has been presented by a recent study on crowdsourcing for Wikipedia. The authors found that an elite circle of a few dominates the discussion and is especially influential (Lee & Seo 2016). In our study, ideas from Top20 users seem to be immune against any negative comments whether from other Top20 users or outsiders. On the contrary, they even seem to profit from negative comments they get from raising stars.

The effects on the winning chances of an idea are the immediate consequences of sabotage behavior. The second step in the analysis was targeted to find out the long-term consequences on the targeted person and its further participation and contribution behavior on the platform. We found that received traffic, likes, positive or negative comments, increase the traffic and the activity of platform members in the consecutive month. Whether this effect is stable over several months has to be investigated further. Studies from other domains (e.g., Youtube) confirm this positive attention spiral (Huberman et al. 2009), where attention leads to further activity on the platform.
Managerial Implications

These results have important implications for the managerial practice of crowdsourcing competitions. First, providers of crowdsourcing platforms or idea competitions have to be aware that “Top Innovators” lists are a double-edged sword. On the one hand, they are a perfect motivator for members to be constantly active and to submit contributions on a regular basis; on the other hand, these lists create fierce competition among contestants, inducing some of them to misuse interaction channels or even to sabotage other members.

The platform provider should therefore carefully monitor the general climate within the community in order to anticipate when the whole atmosphere is in danger of becoming overly negative, affecting the users’ willingness to participate further. The finding that an elite circle is dominating the whole crowd may also limit the heterogeneity benefits of crowdsourcing itself. Platform managers therefore must be aware that the Top Innovators of their lists may produce more of the same (as already suggested by other studies, e.g. Bayus 2013), and they should advise their clients to appreciate the full extent of ideas submitted, regardless of the rank of the member in the various innovator lists. Furthermore, it could be advisable for platform managers to statistically monitor the activities among members and to create an early-warning system when the overall level of activities drops under a certain threshold.

Limitations

Our research is based on log file data from one crowdsourcing platform. We therefore cannot generalize our results to other platforms of this type. Furthermore, it is possible that sabotage behavior has some long-term consequences and that, after a certain amount of sabotage attacks, recipients withdraw from the platform. This will be further investigated.
LITERATURE


