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Crowdsourced Innovation: How Community Managers Affect Crowd Activities*

Abstract

In this study, we investigate whether and to what extent community managers in online collaborative communities can stimulate crowd activities through their engagement. Using a novel data set of 22 large online idea crowdsourcing campaigns, we find that active engagement of community managers positively affects crowd activities in an inverted U-shaped manner. Moreover, we evidence that intellectual stimulation by managers increases community participation, while individual consideration of users has no impact on user activities. Finally, the data reveal that community manager activities that require more effort, such as media file uploads instead of simple written comments, have a larger effect on crowd participation.

Keywords: crowdsourcing, open innovation, crowdsourced innovation, crowdworking, ideation, managerial attention

JEL classification: J21, J22, L86, M21, M54, O31

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1. Introduction

Users innovate because they expect to personally benefit from an innovation in the future (von Hippel 1988) either by producing the innovation themselves (Baldwin et al. 2006, Shah and Tripsas 2007, Haefliger et al. 2010, Block et al. 2016) or by passing the innovation on to a manufacturer that organizes the production (von Hippel et al. 1999). In recent years, user innovation has become digitalized and, as such, has become a commodity that organizations can initiate independently or in cooperation with specialized software vendors via the Internet. Consequently, online crowdsourcing of ideas, which is also referred to as *crowdsourced innovation* (van Delden 2014) or *crowdsourced ideation* (Huang et al. 2014), has become an important tool for large and medium-sized organizations to outsource the development of new products and services in collaboration with (potential) users, customers, and employees.

Prior research on the crowdsourcing of ideas has mostly focused on the motives of individual users and the likelihood that their ideas are implemented. Dahl et al. (2015) show that even consumers who do not participate in the innovation process prefer to buy from user- rather than designer-driven firms, because they feel empowered and identify more strongly with the organization. Using data from the Dell IdeaStorm Community, Bayus (2013) finds that serial ideators are more likely to generate an idea that the organization finds valuable. However, ideas of serial ideators are often similar to those they proposed previously. Moreover, if user innovations are commercialized, ideators face an externality, as others may gain from the development of the product. Using data from Finland, de Jong et al. (2015) show that ideators are less likely to invest in supporting diffusion of a new product or service.

Another strand of literature related to online crowdsourcing has investigated the development of software algorithms through crowd contests (Boudreau et al. 2011, Erat and Kirshnan 2012, Boudreau et al. 2016), the production of application software programs (Boudreau 2012), and the efforts of crowd complementors for computer game platforms (Boudreau and Jeppesen 2015). The focus of these studies is mostly on the impact of economic variables such as the number of competitors, the prize allocation mechanism, and network effects on crowd participation and performance. Still, little is known about the functioning of online collaborative communities. This lack of research on collaborative communities is mostly due to a lack of data, which stems from the fact that collaborative communities are often closed user communities that a firm or software vendor manages. A notable exception is Schemmann et al. (2016), who investigate the characteristics that determine whether an idea is implemented by an international beverage producer. They find that the motivation of an ideator does not influence the likelihood that an idea is implemented. Instead, paying attention to the ideas of others, the popularity of an idea, and its potential innovativeness are important for implementation.

In this article, we use a novel data set that allows us to investigate the crowdsourcing of ideas of multiple collaborative communities from large and medium-sized firms and across various sectors. Unlike previous studies on the crowdsourcing of ideas, we do not focus on users' motives or the success of proposed ideas, but rather on whether and how community managers can motivate the crowd to participate in the first place. Given that online crowdsourcing platforms constitute two-sided markets, attracting as many users as possible appears crucial for platform success. To answer our research question, we use a data set of 22 large-scale campaigns that were run on two online idea crowdsourcing platforms. We gathered the data from a software vendor that provides white-label crowdsourcing platforms to major international and medium-sized enterprises, among them manufacturing companies from automotive, cosmetics, outdoor, and other sectors. Overall, we find that the engagement of community managers has a positive effect on crowd activities. More precisely, we observe an inverted U-shaped pattern, which suggests that moderate but steady manager activities (i.e., eight to nine contributions per day) are an adequate measure to enhance crowd participation. Moreover, we evidence that intellectual stimulation by the community manager significantly increases community participation, while the manager's individual consideration of users has no impact on the total number of user activities. Our data further reveal that users of collaborative communities engage in these activities to a certain extent also during regular working times, which raises the question whether these individuals have a traditional employment contract. Finally, we use propensity score matching to test the causal relationship between manager engagement and crowd participation.

Our study contributes to extant literature in three ways. First, while most studies examine the type of ideators important for successful idea creation and the factors that lead to the implementation of ideas, we analyze how initiators of a crowdsourcing project can contribute to a successful campaign. In particular, we evaluate the role of the community manager in attracting contributions by the crowd. Second, we investigate not only *whether* community managers elicit crowd participation but also *how* they should ideally behave to foster online idea creation. Moreover, we provide insights into how the crowd responds to activities by the community manager. Third, we contribute to the literature on the dynamics of crowd behavior. While the dynamics of the crowd have recently been investigated in reward-based crowdfunding (Kuppuswamy and Bayus 2018) and equity crowdfunding (Hornuf and Schwienbacher 2018), the dynamics of online idea creation are largely underresearched.

The structure of this article is as follows: In section 2, we outline the theoretical background and derive testable hypotheses. In section 3, we describe our data set and explain how online crowdsourcing works on the platforms we analyze. Section 4 presents the methodology. Section 5 summarizes the empirical results, and section 6 concludes.

2. Theory and Hypotheses

2.1. Online Idea Crowdsourcing

In online crowdsourcing, a group of individuals with diverse views and skills is exposed to a problem-solving task by a commercial company. The company, which is also referred to as the online crowdsourcing *sponsor*, identifies the problem and posts it on an online crowdsourcing platform. The sponsor can either use an established online crowdsourcing platform such as Amazon Mechanical Turk or set up its own platform. In case the sponsor establishes its own platform, it can either program it itself or use a white-label solution by a software vendor. In the latter case, the community might be recruited by the sponsor or the software vendor provides a community from other online crowdsourcing projects previously run on the white-label solution. Furthermore, according to Boudreau and Lakhani (2013), online crowdsourcing can take four different forms: crowd contests, crowd complementors, crowd labor markets, and crowd collaborative communities.

In a *crowd contest*, the sponsor offers a prize, which often takes the form of cash, and only the winner of the contest receives the prize, with the remaining crowd missing out. Typical examples of crowd contest platforms are HYVE, Tongal, TopCoder, and Kaggle. These platforms are particularly helpful if the sponsor wants to solve a design or software coding problem and needs help with community management, intellectual property, and payment issues (Boudreau and Lakhani 2013). *Crowd complementors* create innovations that can serve as complements to the original platform. Well-known examples are applications that can be used in combination with mobile devices such as phones or tablets. *Crowd labor markets* constitute markets in which micro tasks, such as the renaming of files or the screening of pictures, are contracted between a sponsor and individual crowd workers. An example of such a crowdworking task is the analysis of satellite images on Amazon Mechanical Turk (Maisonneuve and Chopard 2012). Finally, *crowd collaborative communities* work together to solve a specific problem. In these communities, the platform must coordinate the work of individual members to make online crowdsourcing successful. Online crowdsourcing through crowd collaborative communities is often curated by the respective sponsor. Because sponsors have typically not specialized in setting up online crowdsourcing platforms, they often resort to specialized software vendors to create and manage a collaborative community. Examples of companies that have used collaborative communities are Coty, Ford, IBM, and Lego. Often, these communities are intrinsically motivated or seek the recognition of the community. Cash prizes can also be awarded to these communities but are not particularly common.

The communities we investigate herein fall under the category of crowd collaborative communities. None of the sponsors offered a cash prize, though the software would have theoretically made this possible. Nevertheless, in some cases, the community received the product to experiment and test the ideas at home. However, the products delivered were not the final products and did not resemble a perk valued for consumption.

2.2. Derivation of Hypotheses

On the online crowdsourcing platform we investigate, community members can post as many suggestions and comments as they want. A community manager is charged with screening all user activities. Comments remain on the platform if they contribute in some way to the development of the idea and product. Redundant suggestions or comments such as “I had the same idea” are deleted or merged. The community manager can also post suggestions and comments and thereby encourage the community to get involved. Akcigit et al. (2018) show that getting involved and interacting with others is important because in this way inventors learn and generate knowledge. Because the attention of the crowd is a scare resource, the community manager plays an important role in online idea crowdsourcing. Research on consumer behavior on the Internet, for example, shows that information on the Internet is often so plentiful that the attention of the community decreases over time (Wu and Huberman 2007, Hodas and Lerman 2013). Attention in online communities therefore often follows an L-shaped pattern (Hornuf and Schwienbacher 2018, Kuppuswamy and Bayus 2018).

Managerial attention can be regarded as a technology that recognizes worker performance (Halac and Prat 2016). Workers appreciate this attention because it can lead to recognition of their performance, which they appreciate for either psychological or financial reasons. As a result, the engagement and performance of workers increase with the attention of managers (Harter et al. 2002). Comments by the community manager, who takes a moderating role in the online crowdsourcing campaign, might trigger the attention of the community. Social exchange theory (Blau 1964) argues that leader–member exchanges account for work experiences and ultimately work outcomes. Community managers can act like supervisors in online communities who not only are capable of banning specific contributions or community members but also might motivate the crowd through suggestions, comments, and the provision of media files. In other words, community managers can attract attention and provide valuable resources that help the crowd achieve a goal and desirable outcomes in an online community. In a traditional workplace, resources provided by community managers include augmented communication, clearly defined roles, the fostering of workers' self-esteem, increased knowledge, and the provision of social support (Liden et al. 1997, Mueller and Lee 2002).

In online communities, the community manager's capacity to attract the community's attention might be limited. While engaging with the community can give the community the feeling that member suggestions and comments are appreciated and valued, the engagement of the community manager might only have marginal positive returns to the community. In the most extreme case, the community manager can offer so many suggestions and comments that the creative process of the community is severely reduced. Thus, community participation might increase with a decreasing rate of community manager engagement. We thus formulate the following two hypotheses:

H1a: The community manager's engagement fosters community participation.

H1b: The impact of the community manager on community participation follows an inverted U-shaped pattern.

The impact of the community manager on community participation might depend not only on the *extent* of his or her suggestions and comments but also on the *content* of these factors. The community manager takes the role of a community leader in the online crowdsourcing community, with the community members acting as followers. In particular, community managers have the responsibility to motivate the online community to generate many novel and creative ideas for the development of a product. Leadership research shows that the behavior of a leader is closely related to the creative performance of employees (Martins and Martins 2002, Jaussi and Dionne 2003, Zerfass and Huck 2007). Especially transformational leadership is a relevant predictor of employees' creative performance (Elkins and Keller 2003, Nemanich and Keller 2007, Gumusluoglu and Ilsev 2009). In an early contribution, Sosik et al. (1998) showed that transformational leadership enhances creative ideas and solutions of individuals working in computer-mediated groups.

Moreover, *transformational leadership* stimulates employees intellectually, appreciates proposals, and is directed toward supporting and empowering employees (Sosik et al. 1998, Elkins and Keller 2003, Gumusluoglu and Ilsev 2009). This is reflected in the four dimensions characterizing transformational leadership: (1) *idealized influence*, or leaders' sustainable impact by gaining respect from followers and having high expectations of both followers and themselves; (2) *inspirational motivation*, or articulating an inspiring vision and optimism to followers to achieve goals; (3) *intellectual stimulation*, or stimulating followers to generate creative ideas and new solutions; and (4) *individualized consideration*, or recognizing followers' needs for performance and growth through individual promotion.

Regarding the generation of creative suggestions and comments, *intellectual stimulation* and *individualized consideration* are key facets of the transformational leadership model (Bass 1985, Judge and Piccolo 2004). Intellectual stimulation includes leadership behaviors that make employees aware of problems and think about these in new ways (Rafferty and Griffin 2004). Intellectual stimulation helps generate an open and forward-thinking situation within the community and induces members to participate in problem-solving activities (Zhou et al. 2012).

Individualized consideration of community members' prior comments or ideas is a form of recognizing their abilities as well as their comments' usefulness, which users might reciprocate by exerting higher efforts and contributing more regularly (Ellingsen and Johannesson 2007, Dur 2009). However, both these theoretical considerations and the experimental studies that confirm the importance of appreciation for work motivation (Bradler and Neckermann 2016, Kirchler and Palan 2018) pertain to traditional work environments and, more important, to a direct employer–employee relationship in which workers respond to appreciation they have received themselves. Given the size of collaborative crowd communities, it is unlikely that a manager can appreciate the contributions of all community members. Thus, individual consideration in this setting might not have the expected positive effect, especially in larger communities. Even if members were to view a manager's appreciation as a symbolic award to compete for (see, e.g., Kosfeld and Neckermann 2011), large communities are associated with a low probability of winning this kind of competition, so recognition of one crowdworker is not likely to enhance participation by others.

H2a: Community managers' intellectual stimulation is associated with a larger number of community suggestions and comments.

H2b: Individual consideration is positively associated with crowd participation but only in small crowd communities.

3. Data and Empirical Specification

3.1 Data

We use data on crowdsourced innovation projects operated by 22 large and medium-sized international companies between 2011 and 2016. The data came from a large crowdsourcing software vendor that has developed two similar types of white-label solutions of platforms that differ to some extent in their layout and the type of projects they have attracted, but not their basic software features. Campaigns on platform type 1 (n = 15) differ in product categories, while campaign categories on platform type 2 (n = 7) are rather similar. Most projects are split into two types of phases, the so-called suggestion and voting phases. During the suggestion phase, users give suggestions and comments. Suggestions are users' written statements outlining ideas for the respective product. Comments are users' written statements related to other users' suggestions. To better express their ideas, users can also upload media files such as photos or videos. After the suggestion phase, the community commonly votes on the suggestions previously made. In most projects, users are also allowed to make suggestions and to comment during the voting phase. At the end of the voting phase, another suggestion phase can transpire, for example, to further develop or combine previous ideas. The longest-running project covers eight phases (four suggestions phases, each followed by a voting phase). Community managers can participate in the same way as users: they can make suggestions or comment, upload media, and vote for the suggestions they like. In their role as community managers, they can also delete inappropriate suggestions or comments and consolidate suggestions or comments that are rather similar. Furthermore, community managers can inquire about whether suggestions have been fully understood and motivate the crowd to engage in the project.

The data contain detailed information on each activity that has been executed during a project phase. From these data, we construct a panel data set by aggregating the activities undertaken on a single day in the course of a particular project. Thus, for each project, we have as many observations as days the project was running. As all kinds of user activities are potentially important for the innovation generating process, our main dependent variable to analyze the impact of an actively involved community manager on users' motivation to exert effort is the sum of suggestions, comments, and media uploads, which we call the number of user activities. To test H1a and H1b, we consider three explanatory variables of interest. First, we construct the number of manager activities as we previously did with the number of user activities. Second, we investigate suggestions, comments, and media uploads independently.

Third, as we consider the degree to which the community manager engages with the crowd, we use the length of suggestions and comments as an alternative explanatory variable.

To measure the content of community managers' contributions, we developed a coding system that categorizes the information contained in the comments. In a first step, we generated an initial list of comment categories based on our prior knowledge and research from the transformational leadership literature (Bass 1985, Bass and Riggio 2006). In a second step, we merged similar categories and then developed a system of categories with higher dimensions (Miles and Huberman 1994, Gioia et al. 2012). Our final coding system consists of five categories of manager comments: *appreciation*, *feedback*, *information*, *motivation*, and *intellectual stimulation*.

The category *appreciation* contains community manager comments that value user comments and comments with which the community manager attempts to develop a positive relationship with the crowd. If the community manager attempts to clarify suggestions and comments by users or poses a comprehension question, we code this in the category *feedback*. In case the community manager gives the crowd new information about the product or other product descriptions, we code this in the category *information*. The category *motivation* contains comments in which the community manager encourages the crowd to participate or actively asks for help and support. *Intellectual stimulation* contains all the manager comments questioning and challenging community members to generate new ideas and write comments. Table A.1 in the Appendix provides a detailed overview of the categories, including examples.

To ensure that our coding system was reliable and coherent, we created detailed explanations for each category. Then, an external researcher not involved in the project initially coded 20% of the activities; this allowed us to ensure that the coding categories were exhaustive and that they had a high degree of objectivity. The interrater reliability using Cohen's kappa indicated good agreement between us and the external researcher (Landis and Koch 1977, Fleiss et al. 2003). To achieve even greater consistency in the coding, we discussed the coding system with the external researcher and adapted it when necessary. Afterward, we again coded all 100 suggestions and 2241 comments and conducted another interrater reliability analysis to ensure coding consistency between us. Cohen's kappa was 0.832, indicating good to excellent agreement between us and the external researcher. Finally, we decided to qualify only those comments that were in line with the respective category, if both researchers agreed that a comment belonged to the respective category.

3.2 Empirical Specification

To identify the effect of the community manager on crowd participation, we examine the number of crowd contributions—suggestions, comments, and media uploads—in an online idea crowdsourcing campaign on a given day. Because our dependent variable consists of count data and the unconditional variance of the dependent variable is larger than its mean, we specified a negative binomial model. Our data are available for every day of the project period, so we use a panel data model that can account for the cross-sectional and time-dependent nature of our aggregated data. Conducting a Hausman test led us to dismiss the random-effects model as being inconsistent. We therefore adopted a fixed-effects negative binomial (FENB) estimator. The FENB model has the advantage of removing any unobserved, time-invariant heterogeneity for idea crowdsourcing campaigns. For example, the project initiator, the project purpose, potential rewards, or the personal characteristics of the community manager will be differenced out.

In taking our hypotheses and statistical considerations into account, we specify the following baseline equation:

$$\Pr(y_{i1}, y_{i2}, \ldots, y_{iT}) = F(\textit{manager activities}_{it} + \textit{platform}_{i} + \textit{voting phase}_{i} + \textit{user activities}_{it-1} + \textit{project}_{i}),$$

where y is the number of crowd contributions to project i on day t of the project cycle and F(.) denotes a negative binomial distribution function as in Baltagi (2008). As described previously, *manager activities*$_{it}$ is the number of community manager contributions (suggestions, comments, and media uploads) to project i on day t. To account for unobserved, time-variant heterogeneity, we include additional control variables. First, *platform*$_{i}$ indicates whether the campaign was run on one of the two standard white-label solutions the software vendor provides.[1] Second, *voting phase*$_{i}$ is a dummy for the project phases in which users are allowed to vote for their preferred suggestions. Third, *user activities*$_{it-1}$ is the number of activities (i.e., suggestions, comments, and media uploads) in project i on the previous day. Because users can also respond to other users' contributions and given the potential herding behavior of the crowd (Hornuf and Schwienbacher 2018, Kuppuswamy and Bayus 2018), it seems reasonable that the number of activities on a given day also depends on the number of activities in the previous day. The inclusion of the lagged number of user contributions as

[1] To check for possibly heterogeneous effects of manager activities on user contributions, we also include a platform dummy variable as well as an interaction term between platform and manager activities in certain specifications.

control variable results in the loss of 73 observations due to not having a previous day at the beginning of most phases.[2] Finally, $project_i$ captures the project fixed effects.

In addition, we consider dummies for weekdays, as the crowd might have more time and be more motivated to support a project during the weekend. We also include dummy variables for each decile of the total project length, separated for three different types of projects (projects up to one month, up to two months, and longer than two months). This approach is in line with Hornuf and Schwienbacher (2018) and Kuppuswamy and Bayus (2018), who include a vector of dummies indicating the first and last seven days of the campaign cycle to capture differences in contribution behavior across the project cycle.

4. Results

4.1. Descriptive Statistics

In total, the 22 projects cover 1124 days of observation. The project length varies between 16 to 127 days and its average is 72.04 days (standard deviation = 31.53). The number of active users (i.e., those who write suggestions and comments or upload media) varies between projects, from 16 users to 873 users per project. In 72.7% of the projects, there are two suggestion phases, each followed by a voting phase. The average length of a suggestion phase is 19.17 days, whereas a voting phase is shorter, with only 7.24 days on average. As already indicated, the two platforms on which the projects are operated differ slightly in the types of projects, and thus the intensity of both user and manager activities also differs between the two, as Table 1 illustrates. Because platform 2 is the more active one, we also check for heterogeneous effects of manager activities in our econometric analysis.

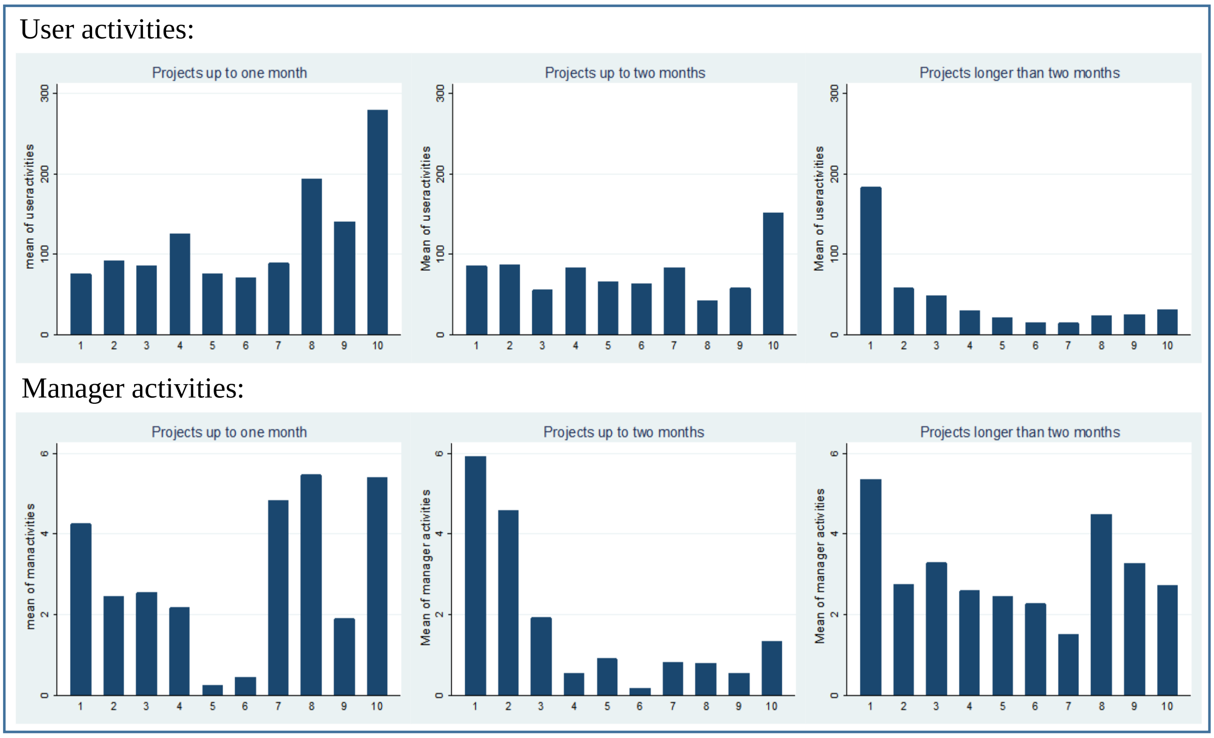
Table 1. Differences between Platforms

	Suggestions	Comments	Media uploaded	Sum of activities	Ø per project		Votes	Ø per project
Platform 1:								
User	4,347	13,476	2,544	20,367	1,357.80		6,315	421.00
Manager	31	1,519	0	1,550	103.33		286	19.07
Platform 2:								
User	13,252	20,902	6,862	41,016	5,858.00		36,868	5,266.86
Manager	69	722	108	899	128.43		1,473	210.43

[2] As a robustness check, we substituted the lagged missing values with a value of 0. The reported results remain qualitatively and quantitatively the same.

Regarding the distribution of user and manager activities by deciles of a project,[3] we find rather diverse patterns depending on the total project length. Figure 1 illustrates these patterns for short projects that last up to one month, projects of medium length with up to two months, and long-running projects with a project period of more than two months.[4] The first two categories show a similar pattern for user activities with rather stable but low-level contributions at the beginning of the project and an increase in activities at the end, which suggests that users engage in some form of sniping and use their last chance to contribute to the project. However, the opposite is true for long-running projects. Given that users know how long a project is running, they might anticipate that they will not contribute over the whole time horizon and exert their efforts only at the beginning. These different patterns make it necessary to control for each decile of each of the three categories in our econometric analysis.

Figure 1. Distribution of Activities by Project Length



Notes. Excluding voting phases.

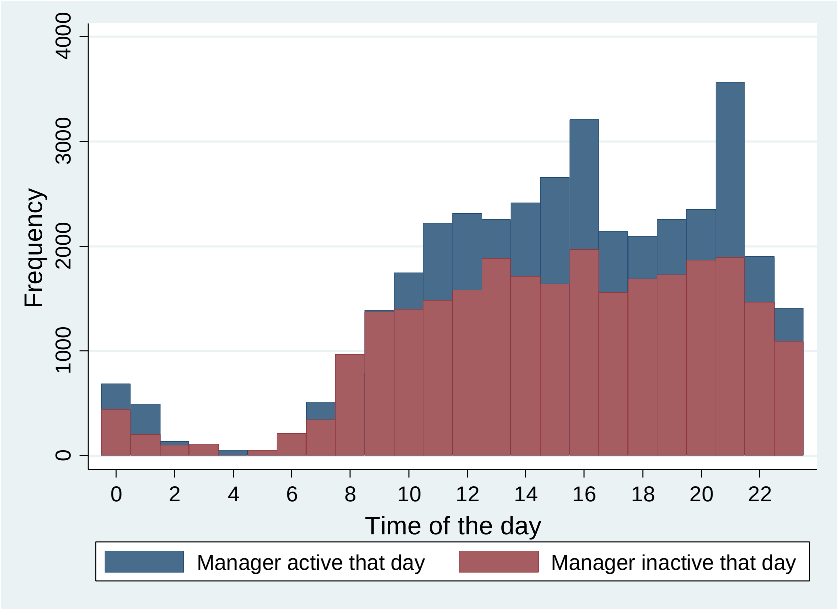
[3] Given the variations in project length, we split the entire project duration into deciles so that the projects are comparable to each other.

[4] Although users are still allowed to suggest, comment, and upload media during voting phases, we observe only 1641 activities in such phases, which is less than 3% of the overall user activities. Thus, we exclude voting phases in Figure 1. Given that a project usually ends with a voting phase, the inclusion of these phases would especially distort the descriptives for the last decile of the project, as we show in Figure A.1 of the Appendix.

Turning to the number of manager activities, we find that managers are inactive in 66.4% of campaign days (72.0% if voting phases are included). Conditional on being active at least once per day, the average number of activities is 7.77 (with 12.00 standard deviation). Figure 1 shows that the patterns for users and managers differ. At first glance, the descriptive statistics suggest that active project managers do not induce more user contributions. The same is true for the scatterplots illustrating both the sum of manager and user activities, either on the daily level or aggregated on the project level (see Appendix, Figure A.2). However, we find that the average number of user activities is 30.54 per day if no manager is active, whereas this number rises to 116.43 user contributions if the project manager was active at least once during that day.

Regarding the distribution of user activities during the course of a day, as illustrated in Figure 2, we observe that the number of user activities is higher at basically every point in time if the community manager was active at least once during that day. Thus, the data suggest that there is a nonlinear relationship between manager and user activities, which we investigate further in the following section. In addition to the differences between days with and without a manager being active, the figure delivers other important insights into the communities' overall behavior: except for the hours in the middle of the night, the users are very active even at times when most employees should be at work (roughly between 8 A.M. and 4 P.M.). Given that there is no cash prize for participating in the community, participation cannot be considered an alternative employment opportunity. As such, we interpret this pattern in at least two ways. First, regularly employed individuals could be highly intrinsically motivated to contribute to the innovation generating process such that they might even be willing to sacrifice working or break times for the collaborative communities. Second, some users might not have a regular job and contribute during their spare time.

Figure 2. Number of User Activities over the Course of the Day



4.2. Community Manager Impact on User Contributions

Table 2 summarizes the main results obtained from regression analyses that investigate the impact of community managers on user activities. Specification (1) gives the incidence rate ratio (IRR) for the number of manager activities on a given day and shows that manager activities do have a highly statistically significant impact on the number of user activities. Although a 1.7% increase in user activities due to only one additional manager activity seems to be a remarkable effect, this effect is rather negligible when compared with the IRR obtained from specification (2), in which we substitute the number of manager activities by a dummy variable for whether a manager is active on a given day or not.

We find that when a project manager is active at least once per day, the total number of user activities increases by almost 50% compared with days without any manager activities, which supports the descriptive evidence of a nonlinear relationship between the number of manager and user activities. This result holds even when a manager was active already the previous day in specification (3) and excluding the voting phases in specification (4). Given that a user's contribution might be a response to a manager's comment from the previous day, the estimated effect of 48% in specification (2) should be the upper bound of how much a manager can raise user contributions. Therefore, we include lagged manager activity (dummy variable) in specification (3), though the point estimate of a manager being active on the current day barely changes. Moreover, we find that the lagged variable is also highly significant. The estimated IRR shows that even the day after a manager was active, his or her contributions raise user activities by 22%.

Table 2. Main Regression Results

	(1)	(2)	(3)	(4)
N° of manager activities	1.017*** (0.004)	--	--	--
Platform 2 × N° of manager activities	0.996 (0.005)	--	--	--
Manager active (yes/no)	--	1.480*** (0.122)	1.454*** (0.120)	1.390*** (0.115)
Platform 2 × Manager active	--	1.054 (0.136)	1.071 (0.137)	1.124 (0.137)
Platform 2	1.234* (0.154)	1.159 (0.154)	1.149 (0.153)	1.482*** (0.203)
Manager was active the previous day	--	--	1.219*** (0.081)	1.201*** (0.078)
N° of user activities the previous day	1.002*** (0.000)	1.002*** (0.000)	1.002*** (0.000)	1.002*** (0.000)
Voting phase	0.017*** (0.005)	0.019*** (0.006)	0.020*** (0.006)	--
Constant	0.579** (0.131)	0.541*** (0.122)	0.523*** (0.118)	0.586*** (0.130)
Additional Controls				
Day of the week	✓	✓	✓	✓
Deciles of total project length	✓	✓	✓	✓
Observations	1051	1051	1051	871
Wald χ^2	725.91	729.16	740.41	687.19
Prob > χ^2	0.000	0.000	0.000	0.000

Notes: The dependent variable is the number of user activities on a given day. The table reports IRRs obtained from the FENB (standard errors in parentheses). Significance levels are denoted as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

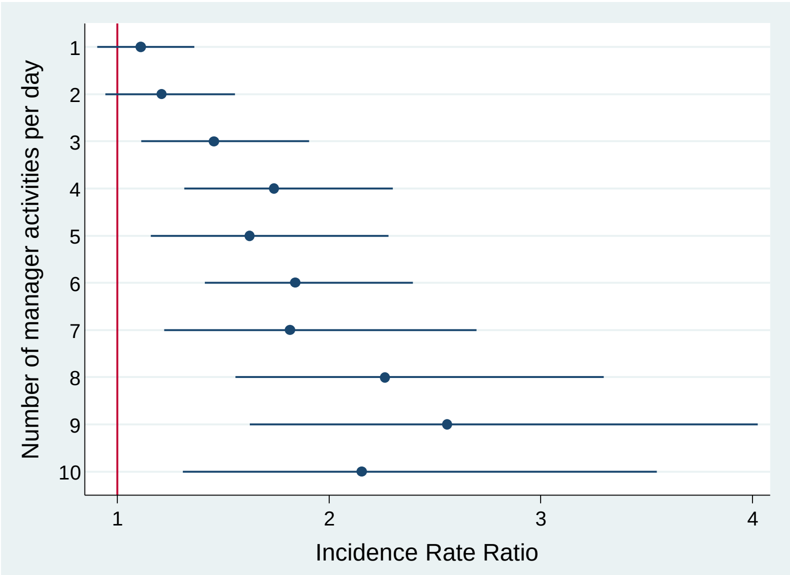
Although it is impossible to judge the quality of each contribution, we might hypothesize that the longer a comment or suggestion is, the more elaborated the user's thoughts might be. To investigate whether the increasing quantity of contributions is not at the expense of their quality, we estimate specifications (1)–(4) using the total length of suggestions and comments (number of words) as a proxy for the quality of user activities. The results are both qualitatively and quantitatively comparable to Table 2; IRRs are even slightly larger (see Appendix Table A.2). Thus, the data strongly support H1a that a community manager fosters community activities.

Regarding the control variables of our baseline model, we find that the more contributions users provided on the previous day, the higher is the number of contributions on the current day. During voting phases, users are clearly less active in making suggestions, commenting, or uploading media. Whereas users are significantly less active on weekends, we do not observe huge differences across weekdays. We find only a minor tendency for activities to decline slightly on Fridays, the beginning of the weekend. Although we use campaign fixed effects, which should capture the overall higher contribution level on platform 2, we still find a positive and statistically significant estimate for this platform in two of the four specifications. Conversely, none of the interaction terms (platform 2 × manager activities) are significant. Thus, there is a positive impact of manager activities on user contributions for both platforms, which is also similar in size. As such, we leave out this interaction term to simplify the model in the following analyses.

As the different estimates for the number of manager activities and an active manager in general indicate a nonlinear relationship between the intensity of manager activities and user contributions, we estimate IRRs separately for different numbers of manager activities per day. Figure 3 illustrates that one or two manager contributions per day do not significantly increase user contributions. Graphically, we show that the more active a manager is on a given day, the stronger is the effect on user contributions. However, only the point estimates for eight and nine contributions per day differ statistically significantly from contributing only three times per day ($p = 0.051$ and $p = 0.031$, respectively).

We estimate the IRRs only for up to 10 contributions per day, as we only have 62 observations in which the number of contributions is somewhere between 11 and 120. Pooling the remaining observations into broader intervals and running a similar regression, we find that the IRR remains rather stable somewhat below 2 in the case of up to 20 contributions per day, and the estimated IRR for the interval from 21 up to 30 activities shrinks to 1.041. Thus, it is important for community managers to be active on as many days during the campaign as possible, but a moderate activity level is sufficient to stimulate user activities. Moreover, we estimate the impact of being active depending on the length of the suggestion phase, which ranges from four to 43 days, with a median of 16 days. We find that an active manager has a highly significant and positive impact on user activities in case of suggestion phases that last both below and above the median number of days (1.441 vs. 1.480, both *p*s < 0.01), suggesting that regular manager activities can boost users' motivation to contribute even in long-lasting project phases. These results provide support for H1b that a manager's impact on community participation follows an inverted U-shaped pattern.

Figure 3. The Impact of Additional Manager Activities on User Activities



Notes. The estimates are based on specification (3) from Table 2 but exclude the interaction term between platform 2 and manager activities. Observations with more than 10 manager activities per day are dropped, resulting in 994 observations.

4.3. The impact of Content on User Contributions

After establishing a strong and robust impact of manager contributions on user activities in general, we investigate whether the type of contribution and the concrete content of suggestions and comments play a role in users' responses. As outlined in section 3.1, both managers and users can contribute in terms of suggestions, comments, and media uploads. Given that uploading media, for example, requires more time and effort than posting a comment, which might generate less attention in the community, we might expect the different categories to have a differential impact on user activities. Thus, we estimated our baseline specification in a modified form, adopting novel measures for our dependent variable and the variable of main interest. As Table 3 illustrates, specifications (1) and (2) are unchanged with regard to the dependent variable (the sum of all possible user activities), while the manager activities are split into suggestions, comments, and media uploads. In specifications (3)–(5), we also split user activities into the three different categories. Manager comments and, to an even greater extent (p = 0.107 in specification (2)), manager media are consistently estimated to have an economically highly significant impact on user activities, independent of the kind of activities we consider. Manager suggestions, however, have an impact on user suggestions only. A possible explanation for this is that though users might hesitate to comment on the manager's suggestions, these raise their motivation to come up with a similarly good or even better idea than the manager. However, the results for manager suggestions should be taken with caution because of the rather low number of observations (only 100 suggestions within 1124 project days).

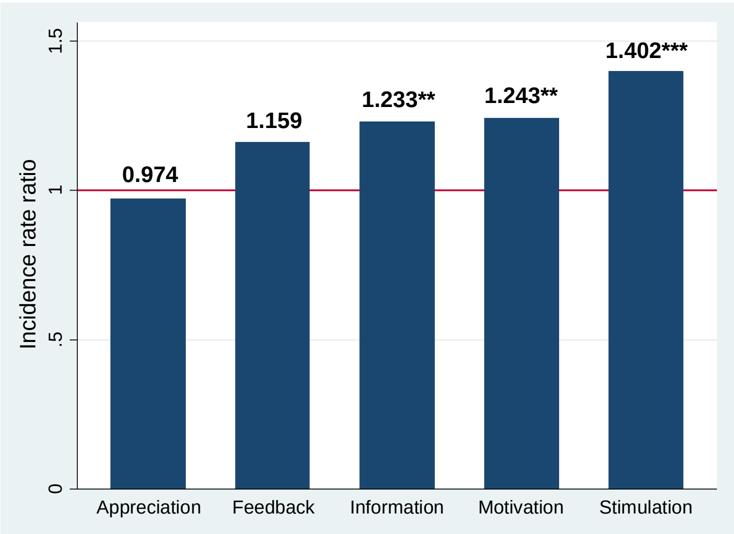
Table 3. Differences among Suggestions, Comments, and Media Uploads

	(1)	(2)	(3)	(4)	(5)
Dependent variable	All user activities	All user activities	User comments only	User suggestions only	User media only
N° of manager comments	1.013*** (0.002)	--	--	--	--
N° of manager suggestions	0.967 (0.050)	--	--	--	--
N° of manager media	1.033 (0.021)	--	--	--	--
Manager suggestions (yes/no)	--	1.019 (0.165)	1.004 (0.160)	1.387* (0.243)	1.632 (0.697)
Manager comments (yes/no)	--	1.472*** (0.098)	1.588*** (0.113)	1.214** (0.093)	1.546*** (0.189)
Manager media (yes/no)	--	2.017*** (0.362)	1.909*** (0.354)	1.737*** (0.360)	1.729* (0.502)
Constant	0.573** (0.137)	0.538*** (0.121)	0.634** (0.144)	0.457*** (0.113)	0.042*** (0.043)
Observations	1051	1051	1051	1051	837
Wald χ^2	743.45	767.39	804.20	401.14	320.54
Prob > χ^2	0.000	0.000	0.000	0.000	0.000

Notes. The dependent variable is the number of user activities on a given day. The table reports IRRs obtained from the FENB (standard errors in parentheses). Controls are identical to specification (3) in Table 2 but exclude the interaction term between platform 2 and manager activities. Significance levels are denoted as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

When examining the content of the managers' suggestions and comments (as described in section 3.1. and in Table A.1 in the Appendix), we observe that managers inform the community members about the latest developments of the project or the product itself (in 78.1% of all days on which the manager is active). Managers are similarly active in valuing user suggestions and comments (75.6%) and are only slightly less active in stimulating suggestions and comments (68.3%). Suggestions and comments that have been coded in the categories feedback and motivation appear infrequently (13.3% and 15.6%, respectively). In line with the transformational leadership model and H2a, Figure 4 shows that stimulating suggestions and comments has a strong impact on overall user activities, with an IRR of 1.402. Likelihood ratio tests, however, do not support the conjecture that stimulation has a greater impact than motivation or information (p = 0.365 and p = 0.368, respectively). Thus, managers are right to provide information (which might be a necessary resource for the development of ideas) and intellectual stimulation, but they should increase their motivational activities.

Figure 4. Does the Content of Manager Activities Matter?



Notes. The estimates are based on specification (3) in Table 2 but exclude the interaction term between platform 2 and manager activities.

Regarding appreciation, our data are only partially in line with our hypothesis 2b: we find a positive impact on crowd participation neither for the whole sample nor for a subsample of smaller communities. Although the sample size becomes very small if we assess only communities with, for example, up to 50 active users, the point estimate is similar to the one we obtain from the full sample. Nevertheless, 50 individuals are still a sizable number and probably larger than a usual working group within a firm, which is under the control of one supervisor or manager. As such, it remains an open question whether the positive impact of workplace appreciation transfers to such an online setting that requires only very small communities. Thus, we find support for H2a, in that intellectual stimulation substantially increases community participation, while individual consideration has no impact on the sum of user activities, even in small crowd communities.

4.4. Causality

Given the observational nature of our data, it could be argued that our results suffer from reverse causality, in that the positive relationship between manager and user activities is due to managers responding to the activities of the crowd. Although we cannot rule this suggestion out completely, at least two findings and one additional test suggest the opposite.

First, specifications (3) and (4) in Table 2 include a lagged dummy variable that measures whether a manager was active on the previous day. As user contributions on the current day cannot influence manager engagement from the previous day and we find a highly significant IRR (1.2) for this lagged variable, the positive relationship between manager and user contributions cannot entirely be driven by user activities causing the manager to respond. Second, if our results do suffer from reverse causality, the content of manager suggestions and comments should not matter. However, we do not find a positive relationship between the two categories feedback and appreciation and crowd participation. Especially the latter should be positively related because a more active crowd generates more opportunities for managers to recognize user contributions.

Finally, we use propensity score matching to estimate the causal effect of a manager being active. We therefore compare only the days on which managers have the same likelihood of being active, by matching one observation from our artificial treatment group (i.e., one day on which a manager was active) with one control group observation when no manager was active that day. In line with Rosenbaum and Rubin (1983), we consider only the observation that has the closest propensity score. We calculate the propensity scores using the same control variables as in our main specification[5]—without the control for a manager being active on that day—and the propensity scores of two matched observations are required to be below the predefined caliper of 0.01. With the one-to-one matching and the caliper restriction, the sample size shrinks to 364 observations, but the density distributions of propensity scores (see Appendix, Figure A.3) and the biases before and after matching (see Appendix, Figure A.4) show better alignment of covariates. Thus, it is only reasonable that the average number of user activities differs, but not as extreme as before, and we still find a

[5] Compared with our main specification, we refrained from controlling for the deciles of project length to avoid an even large loss in sample size. As time trends, however, do play a role in our analysis, we included variables to control for the number of days that have passed since the beginning of the current suggestion phase and an additional dummy for the last day of the phase, as the crowd might behave differently on that special day.

sizable difference between days on which the community manager was active, with an average of 78.46 user activities compared with only 53.80 activities without a manager being active, resulting in an IRR of 1.458 (p = 0.011). Taken together, our findings are unlikely to be due to reverse causality.

5. Discussion and Conclusions

This study extends previous research on crowdsourced innovation, which has largely focused on individual motives to participate in online innovation projects and the likelihood of idea implementation, by analyzing the role of the community manager in crowd participation. Crowd participation is also a relevant component for project success, as a more diversified group of contributors often has better capacities to solve an existing problem (Surowiecki 2004). Using a novel data set from a large crowdsourcing software vendor, we find that managers should optimally be present on a regular basis but not to a maximum extent. Whereas a moderate but persistent number of activities each day significantly foster crowd participation, being active several times a day but only occasionally negatively affects crowd participation. Moreover, managers are well-advised to stimulate the crowd intellectually, to motivate them to contribute, and to provide relevant information about the project. Managers' own suggestions have no impact on crowd activities, though managers should focus on commenting on the crowd's suggestions and on activities that require more effort, such as the inclusion of media files.

The observed patterns regarding the content of managers' activities raise two important questions for future research. First, the data suggest that media uploads have the largest effect on crowd participation. One interpretation is that users value the effort managers' invested in the creation of media files by contributing more actively afterward. However, a media file might be more visible than a single comment. If more users are aware of a manager's activity, more users may also respond to it. Second, we question whether the known positive impact of managers' appreciation in a typical workplace transfers to such an online setting, whether it depends on the size of the community, and what role privacy preferences of users and managers play.

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Appendix

Table A.1. Definition and Examples of Comment Coding

Coding of comments	Examples
Appreciation: The community manager makes comments that value user suggestions and comments. The community manager attempts to develop a positive relationship with the crowd and highlights the relevance of the comments.	a) “True! We can learn a lot from the thin thermos-materials.” b) “Nice pictures :) Thank you for your feedback.” c) “Very nice idea, take a picture of the colors with illumination level z!”
Feedback: The community manager attempts to clarify users’ suggestions and comments or poses a comprehension question.	a) “You would like to have a tighter, more fitted jacket, if I understand you correctly? What precisely was not right with the fit of the jacket especially at the back part? Can you describe that more precisely?” b) “Dear co-developers! Unfortunately, we must tell you that a two-phase shower cannot be realized till autumn.”
Information: The community manager gives the crowd new information about the product or provides product descriptions. The community manager postpones the comment until a later stage of the project.	a) “Hi Monika! You have a great point here. Unfortunately, we only need the concrete theme. On the top left you also see the project overview. Cordially, Moritz” b) “That might be feasibly even without a sliding door. It might be important that the seat at least slightly turn to the outside. Many sit fir with their but in the seat and then turn inside the car.”
Motivation: The community manager encourages the crowd to participate or actively asks for help.	a) “If you have X-BIONIC clothes at home that you can compare with the tester feedback or if you have questions you may want to ask the testers you can join in on the discussion even if you are not a tester. We would be happy to see you around!” b) “If you have templates that we can upload for you, you can also send them via e-mail to [redacted]@plattform.de.”
Intellectual stimulation: The community manager comments by questioning and challenging community members to generate new ideas and write comments. The community manager poses questions regarding the product development, product name, usage, marketing, and value added of the product.	a) “What kind of chest pocket would you prefer? E.g. size, positioning, zipper etc.” b) “Do you have other ideas or needs as to how the jacket could be improved to fit underneath a hard-shell besides the chest pocket?”

Table A.2. Number of Words as Dependent Variable

	(1)	(2)	(3)	(4)
N° of manager activities	1.019***	--	--	--
	(0.004)			
Platform 2 × N° of manager activities	0.997	--	--	--
	(0.005)			
Manager active (yes/no)	--	1.677***	1.654***	1.606***
		(0.146)	(0.143)	(0.140)
Platform 2 × Manager active	--	1.043	1.060	1.070
		(0.140)	(0.141)	(0.142)
Platform 2	1.829***	1.648***	1.656***	1.744***
	(0.234)	(0.225)	(0.226)	(0.240)
Manager was active the previous day	--	--	1.253***	1.224***
			(0.086)	(0.084)
N° of user activities the previous day	1.002***	1.002***	1.002***	1.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Voting phase	0.013***	0.016***	0.017***	--
	(0.004)	(0.005)	(0.005)	
Constant	0.195**	0.189***	0.187***	0.198***
	(0.047)	(0.045)	(0.045)	(0.047)
Additional Controls				
Day of the week	✓	✓	✓	✓
Deciles of total project length	✓	✓	✓	✓
Observations	1051	1051	1051	871
Wald χ^2	889.37	885.07	900.94	696.53
Prob > χ^2	0.000	0.000	0.000	0.000

Notes. The dependent variable is the number of words written by all users on a given day. The table reports IRRs obtained from the FENB (standard errors in parentheses). Significance levels are denoted as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure A.1. User Activities by Deciles of Project Length

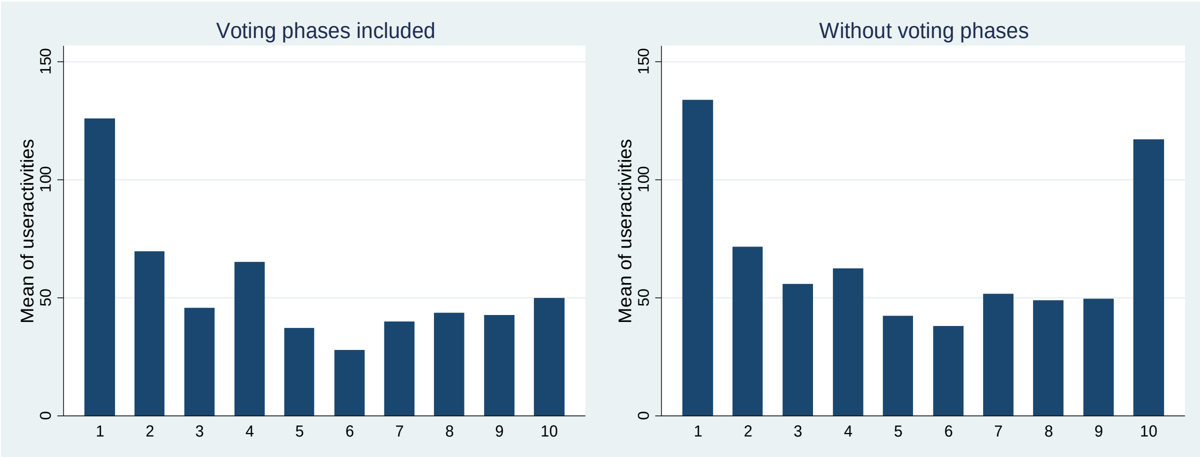


Figure A.2. User and Manager Activities at the Day and Project Levels

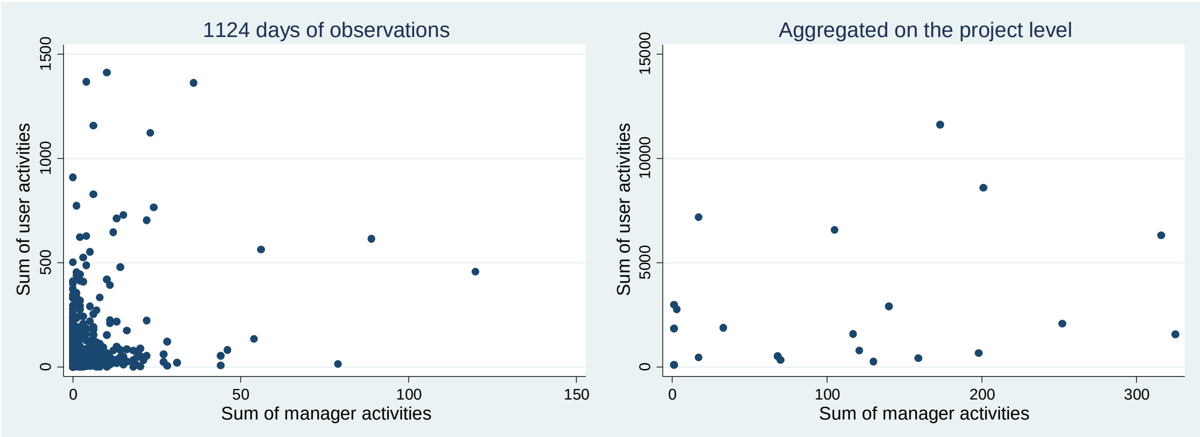
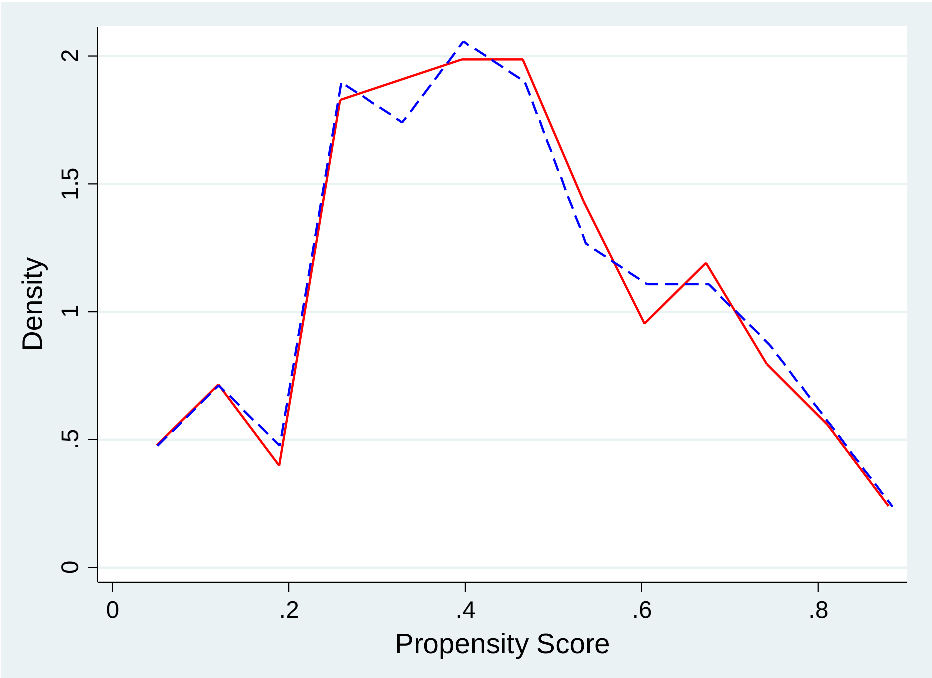
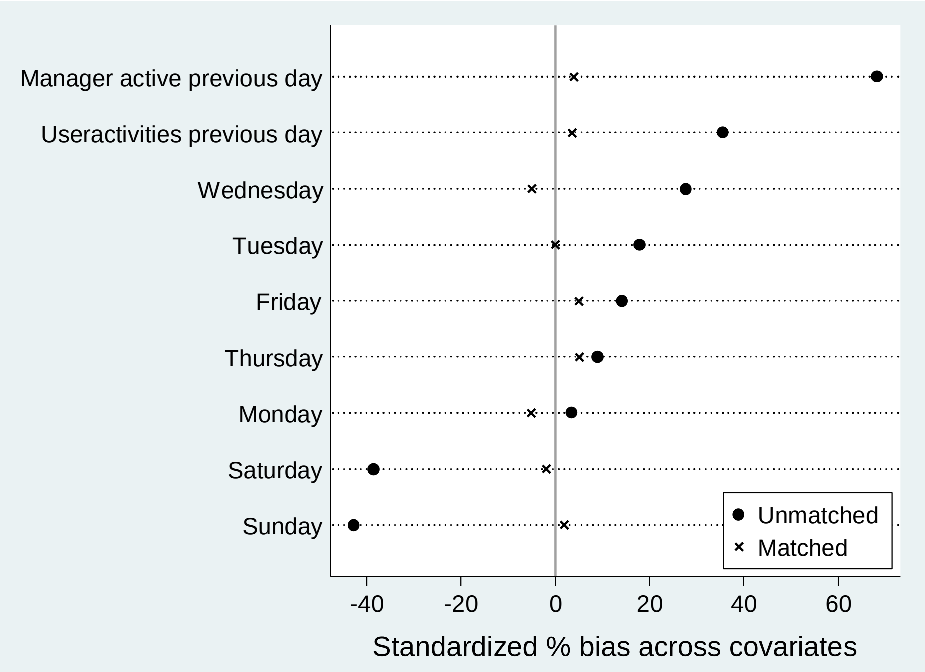


Figure A.3. Density Distribution of Propensity Scores



Notes. The solid red line shows the propensity scores for the treatment group, and the dashed blue line covers the matched control group observations. The propensity scores are estimated on a slightly different set of control variables than our main specification. See footnote 5 for details.

Figure A.4. PSM and Bias Reduction across Covariates



Notes. The figure shows the bias across covariates for the total sample covering 1124 days of observation and for the reduced sample resulting from the matching procedure with 364 days of observations.

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