Motivating User Contributions in Online Knowledge Communities: Virtual Rewards and Reputation

Xiahua Wei
School of Business
University of Washington, Bothell
xhwei@uwashington.edu

Wei Chen
Rady School of Management
University of California, San Diego
wei.chen@rady.ucsd.edu

Kevin Zhu
Rady School of Management
University of California, San Diego
kxzhu@ucsd.edu

Abstract
User contribution determines the success of online knowledge communities. As user contributions are voluntary, many online communities failed due to declining user contributions. Hence, it becomes critical to understand and design mechanisms that are effective to motivate user contributions. This paper studies the effects of two mechanisms, virtual rewards and reputation, on the quantity and quality of user contributions in online community. We analyze user-level panel data from a representative knowledge sharing platform StackExchange.com, and investigate whether these two mechanisms improve the quantity and quality of user contributions. Surprisingly, we find that a user’s reputation does not directly motivate contribution. It is the relative reputation (ranking) that serves as the motivation. This finding highlights the importance of peer effect and social comparison in the incentive design of open collaboration platforms. Our study provides implications for platform designers on how to motivate community participants and build sustainable online knowledge communities.

1. Introduction

The Internet enables knowledge sharing and creation beyond boundaries. Many knowledge communities built online are designed to promote open collaboration and facilitate innovation. Some of them are successful (e.g. Wikipedia, Yahoo! Answers, Facebook Questions). However, many failed due to the lack of effective collaboration among participants [1].

The survival and prosperity of online knowledge communities rely on the quality and quantity of user contributions. Yet, user contributions are voluntary without monetary compensation, and thus online knowledge communities could suffer from the traditional dilemma of public goods [2]. In fact, a common challenge faced by many knowledge communities is the decline of user participations. For example, only 33,276 users contributed to Wikipedia in March 2013, shrinking by 36% from the peak in 2007 [3]. This raises a significant question about how to motivate users to continue contributing. Addressing this challenge requires a deep understanding of the motives of users, and subsequently designing effective incentives to enhance user engagement and sustain collaboration.

In the literature of online communities, membership size and communication activity have been regarded as key factors in community sustainability [4]. Other important factors include trust [5], membership turnover [1], and community commitment [6]. Several mechanisms, such as social comparison and virtual rewards (e.g., points, badges, levels, status), have been proposed to be embedded into the incentive structure [7, 8]. By effectively employing these mechanisms, voluntary contributions to the knowledge community can be induced. However, few prior studies show whether these mechanisms indeed effective to drive user contributions. Our paper attempts to narrow this gap by examining the value of the badge and reputation system on user activities in online knowledge communities.

Specifically, we study two major research questions: (1) Do reputation and virtual rewards affect the quantity and quality of contributions? (2) How do reputation and virtual rewards affect different types of user contributions? We focus on the role of reputation and virtual rewards, because they are the mechanisms that the platform designer could manage.

We address these questions by analyzing a unique matched panel data from 692 users over 17 months on StackExchange, a representative online knowledge community. Using regression discontinuity and difference-in-difference estimation, we find that reputation drives user contributions indirectly. Users contribute not because they want higher reputation and thus more privileges, but because they are motivated by relative reputation (ranking). As such, we provide...
empirical evidence that quantifies the significance of virtual rewards and reputation for community participation and engagement.

The reminder of this paper is organized as follows. We first introduce our research context, review relevant literature on online communities, and develop three hypotheses. We then test our hypotheses and discuss the results. We conclude with major findings and future research directions.

2. Theory and Hypotheses

2.1. Research Context

Our research is conducted in the context of StackExchange.com, a large network of online knowledge communities that rely on voluntary user participation for question and answer (Q&A). Originated from Stack Overflow, a successful Q&A website for programmers, StackExchange is a fast-growing platform. By September 2014, it has built more than 120 communities specialized in various topics, from software programming to cooking, photography, and gaming. On each of these sites, experts and enthusiasts with common interests share their knowledge, and the discussion can be technical and professional.

We choose StackExchange as our empirical setting, because it is a representative online platform of knowledge sharing and collective innovation. User can ask and answer questions, comment on each other’s posts, suggest revisions, and even edit others’ posts when they reach certain level of privileges. A distinctive feature of StackExchange is that it ensures the quality of knowledge by peer editing. Unlike other Q&A websites such as Yahoo! Answers, StackExchange allow qualified users to delete duplicated or inappropriate questions and answers, and edit them so that they are on-topic, relevant and specific. All of these activities are voluntary, but they are essential to creating a collective curation of information that is useful not only to the original questioner, but also for all users who are interested in the topic. This feature can help us understand knowledge collaboration behaviors in a voluntary virtual community. StackExchange provides detailed data about the user actions and interactions in the community. For example, we can observe when a user receives an upvote on his answers, and whether and when his answer has been accepted as the best answer. This kind of detail information at the user level is necessary to address our research questions.

Further, StackExchange uses several mechanisms to motivate user participation. First, the badge system rewards users with badges for specific actions. For instance, users earn a bronze badge of “Autobiographer” when they complete their profiles; users asking a question with 2500 views will earn a silver badge of “Notable Question”; an answer with 100 scores will receive a gold badge of “Great Answers”. A user can earn multiple badges, which are displayed on his profile. Second, StackExchange also has a reputation system. Users gain reputation when their questions or answers are voted up by others. They also gain more privileges after passing certain thresholds of reputations, such as leaving comments, voting down others’ posts, and edit others’ posts, etc.

By using badge and reputation systems that reward certain user contributions at specific levels, designers of online communities can attempt to gear user activities toward particular forms of contribution. On StackExchange or similar Q&A sites where most users want to receive answers and few want to provide them, introducing a badge/reputation for users who have contributed a certain number of answers may direct the community to this under-provided contribution. Similarly, badges for voting can steer users toward providing feedback to maintain the quality of the content. Then the question is, are virtual rewards based on badge system effective to motivate user contribution? Do users contribute because they want to earn more reputations and thus get more privileges in the community? Are higher reputations associated with more contribution and higher-quality contribution? By analyzing how virtual rewards and reputation would affect the contribution behaviors of the users, we hope to provide insights into these motivating mechanisms and their use. As such, we can shed light on how to designing mechanism and manage the community effectively when contribution is voluntary.

2.2. Theoretical Background

An online community is a group of people whose interests overlap and whose actions are partially influenced by this perception in an IT supported virtual space [9, 10]. Online community enables open collaboration, a system of innovation where participants coordinate to co-create a product/service available to all [11]. Examples include open source software projects, and user forum/community aimed at innovation/production (not social interaction). The online knowledge community is a prevalent form of open collaboration for knowledge management, such as Wikipedia and StackExchange. These communities rely on voluntary contributions from members to produce content and accumulate knowledge that is open and free to not only contributors, but also non-contributors. For example, all contributions on
StackExchange are licensed under Creative Commons. In this sense, users are contributing to a public good, which is non-rivalry and non-exclusive. Since everyone can share the benefits, but only those contribute incur the production costs, the public goods usually suffer from free-riding and thus under-provision problems. This “tragedy of the commons” is a classic prediction of the economics theory. Indeed, voluntary cooperation is inherently fragile, even if most people are conditional cooperators [12]. Hence, sustaining voluntary contributions is a key challenge for online knowledge communities, which requires effective institutional designs.

For traditional public goods, tax and monetary incentives are usually prescribed to address this problem [13], rewarding behaviors with positive externalities, and punishing those with negative externalities. However, since people contribute voluntarily in StackExchange, these monetary transfer mechanisms are unavailable. To explore the solution unique to online knowledge communities, we first need to understand why users contribute, so as to design targeting mechanisms that can motivate their contribution.

Motivation theories are useful along this line. The literature on open source software has distinguished and studied the role of intrinsic motivations and extrinsic motivations [14]. Similarly, in online knowledge communities, a user’s intrinsic motivation (e.g., desire for self-achievement) and extrinsic motivation (e.g., social image) may coexist and simultaneously affect individuals’ behavior. The literature of online communities has identified various drivers of user contribution, for example, the enjoyment of reputation and social image [15], self-efficacy and sense of achievement [16, 17], entertainment through social interactions [15, 18], reciprocity [19, 20], social capital [15, 21], and altruism and community interests [6, 9]. Chen et al. (2010) also shows that social comparison could improve the contributions of users who are below the median, though the contributions from high contribution users would decrease as well. Savikhin and Klimeck (2011) find that virtual rewards could increase the contributions, while observational cue does not have a significant effect.

Another useful theory to explain the continuation of user contribution is the online community commitment theory [6, 22]. The theory suggests that participants develop psychological bonds to particular online communities due to three types of commitments: need, affect, and/or obligation. For example, Bateman et al. (2011) find that each commitment has a unique impact on specific actions: need-based commitment predicts thread reading, affect-based commitment predicts reply posting and discussion moderating, and obligation-based commitment predicts only moderating behavior.

The commitment theory provides a coherent framework for competing explanations of user participation in prior studies. The design of virtual rewards and reputation can be built to strengthen these commitments. Badges and reputation play multiple roles. First, they function as a credentialing system, signaling the skills, expertise, achievements, commitment and status of the individuals. The individual may desire to earn more to get public recognition (affect-based reputation). Second, badges and reputation provide incentive functions, as people may direct considerable amounts of effort to pursue them to get more privileges (need-based). Third, senior users with more badges and high reputation benefit from the community and may want to help others in return (obligation-based reciprocity). The focus of our paper is to investigate the ways which badges and reputation affect the extent of user participation in online communities.

The badge and reputation systems can promote certain activities for particular individuals, while discouraging other activities. Hence, designing effective motivating mechanisms in knowledge sharing environment is challenging, because various badges/reputations can simultaneously play different, potentially contradictory roles. The goal of our paper is to frame the virtual rewards and reputations as a design problem, empirically examine various effects of them on user activities in StackExchange, and use these ideas and findings to inform the design of the online knowledge communities. As more and more organizations are leveraging online knowledge forums to promote knowledge flow and manage innovation, we also hope our results provide insights into designing effective knowledge sharing platform in the corporate environment, especially when monetary incentive is absent.

2.3. Hypotheses

StackExchange offers value to users from several different sources. First, people who have questions get high quality answers from the community. However, users who ask questions do not necessarily contribute back unless there is a norm of reciprocity. Second, users value the knowledge accumulated in the community. Third, some of the users have high social preference so they value their own contributions to the community. The public good framework [13] has addressed some of the fundamental issues of contributions to community, but mostly in the lab experiment environment. Instead, we model the user valuation of virtual community using the framework of
public goods, and test it empirically in our research context [8, 13]. We focus on the demand and supply of knowledge, i.e., questions and answers, which are the essential functions for a knowledge sharing platform.

In a simple public good game, risk-neutral players choose a portion of their endowments $e_i$ to contribute to a public good. Each user $i$’s contribution $c_i$ are summed up to represent the value of the knowledge in the community. Users incur costs of spending time and effort to contribute to the community, represented by $c_i$, which is also the effort contributed. Users value the total knowledge contributed to the community $\sum c_j$ with a marginal per capita return (MPCR) $m_i$. Users also value their own contributions to the community according to some social preference (intrinsic motivations such as altruism), represented by $q_i$. Therefore, we specify the utility of a user as

$$\pi_i = e_i - c_i + q_i c_i + m_j \sum c_j$$

The equilibrium in this static setting is to contribute the full endowment $c_i = e_i$, when $(q_i + m_i) > 1$, contribute nothing when $(q_i + m_i) < 1$, and indifferent when $(q_i + m_i) = 1$.

However, users in the community are uncertain about their valuation of their own contributions to and the accumulated knowledge of the community, because it is complicated to assess the value of knowledge. We use two functions to represent the uncertainties of evaluating their own valuation, $f(q_i, b_i, r_i)$ and $g(m_i)$. The effects of different mechanisms go into valuation of users through these functions:

$$\pi_i = e_i - c_i + q_i c_i + f(q_i, b_i, r_i)c_i + g(m_i)\sum c_j$$

In our empirical setting, $b_i$ and $r_i$ correspond to badges and reputation earned by the user, respectively.

Ma and Agarwal (2007) show that self-presentation IT-based features are positively associated with perceived identity verification and thus improve knowledge contribution. The badges and reputations could also cultivate trust [5] and promote community commitment [6]. The literature also suggests that virtual rewards could increase user contributions [8]. Along this logic, we expect similar effects of reputation and badges in our research context. Therefore, we conjecture that $f(q_i, b_i, r_i)$ increases with $b_i$ and $r_i$, and these mechanisms increase the probability of contributions. Hence, we hypothesize the following:

**Hypothesis 1 (H1).** The reputation earned by a user is positively associated with the quantity and quality of his contributions in the subsequent period.

**Hypothesis 2 (H2).** The number of badges earned by a user is positively associated with the quantity and quality of his contributions in the subsequent period.

Another potential reason of user contribution might come from the social context. Users may not response to reputation or badges incentives. Rather, their actions may be induced by peer effects and social comparison on the site. The literature documents a positive link between perceived identity verification and knowledge contribution [9]. Meanwhile, social comparison could increase the efforts of users whose contributions are below the median if this benchmark information is available [7]. As the effect of ranking can go either direction for users with different rankings, we propose the following hypothesis:

**Hypothesis 3 (H3).** The ranking of a user’s reputation is positively/negatively associated with the quantity and quality of her contributions in the subsequent period.

### 3. Data

To test our hypotheses, we collect data from two sites on StackExchange, bicycles.stackexchange.com (b) and cooking.stackexchange.com (c). Topics on these two sites are leisure-related, unlike programming sites where user activities may be driven by career and have the incentive of signaling. We first developed a Java program to collect all the questions, answers, comments, and users’ information from August 2010 to December 2011. We then matched data from the two sites, and construct a matched panel of 692 unique users active on both sites. We use user-month as the unit of analysis, with a total of 6,250 observations.

To measure the relative ranking of reputation, we focus on the first page of user ranking, as it is more directly available for user comparison than all the following pages that need to be clicked through. Figure 1 below provides a screenshot of this ranking page for the cooking site. The page lists 4 users in each row, with a total of 36 users. We define three exclusive dummies Top 4, Top 12 and Top 36.

We also classify virtual rewards into three categories: bronze, silver and gold badges (no user has earned gold badges during the sample period, so this category is omitted).

On such a knowledge sharing community, the quality of questions and answers are crucial. User $i$’s quality of questions in month $t$ is measured by the average number of upvotes he receives for his questions at that time. For his quality of answers, we use two measures: the average number of upvotes he receives for his answers, and the number of his answers accepted by others in month $t$. 

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We also control for the characteristics of users and the site, including how long the user has been registered on the site, how many users are active on the site, and the total number of bounties (reputation award offered by users seeking questions) available on the site. The key variables are described in Table 1 above with descriptive statistics.

### Table 1. Definitions of Key Variables

<table>
<thead>
<tr>
<th>Categories</th>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reputation</td>
<td>Rep</td>
<td>Points of reputations earned by user $i$ in month $t$</td>
<td>7.358</td>
<td>44.292</td>
</tr>
<tr>
<td>Relative Reputation</td>
<td>Top 4</td>
<td>Users whose reputation ranked top 4 on the ranking page</td>
<td>0.002</td>
<td>0.0456</td>
</tr>
<tr>
<td></td>
<td>Top 12</td>
<td>Users whose reputation ranked top 5-12 on the ranking page</td>
<td>0.006</td>
<td>0.080</td>
</tr>
<tr>
<td></td>
<td>Top 36</td>
<td>Users whose reputation ranked top 13-36 on the ranking page</td>
<td>0.015</td>
<td>0.122</td>
</tr>
<tr>
<td>Virtual Rewards</td>
<td>Bronze</td>
<td>Number of bronze badges earned by user $i$ in month $t$</td>
<td>0.216</td>
<td>0.746</td>
</tr>
<tr>
<td></td>
<td>Silver</td>
<td>Number of silver badges earned by user $i$ in month $t$</td>
<td>0.022</td>
<td>0.169</td>
</tr>
<tr>
<td>Contribution Quantity</td>
<td>Questions</td>
<td>Number of questions asked by user $i$ in month $t$</td>
<td>0.058</td>
<td>0.412</td>
</tr>
<tr>
<td></td>
<td>Answers</td>
<td>Number of answers provided by user $i$ in month $t$</td>
<td>0.152</td>
<td>1.207</td>
</tr>
<tr>
<td></td>
<td>Comments</td>
<td>Number of comments provided by user $i$ in month $t$</td>
<td>0.475</td>
<td>4.749</td>
</tr>
<tr>
<td>Contribution Quality</td>
<td>Q Upvotes</td>
<td>Average of the upvotes on the questions by user $i$ in month $t$</td>
<td>0.213</td>
<td>1.404</td>
</tr>
<tr>
<td></td>
<td>A Upvotes</td>
<td>Average of the upvotes on the answers by user $i$ in month $t$</td>
<td>0.133</td>
<td>0.836</td>
</tr>
<tr>
<td></td>
<td>A Accepted</td>
<td>Number of accepted answers provided by user $i$ in month $t$</td>
<td>0.026</td>
<td>0.255</td>
</tr>
<tr>
<td>User/Site Characteristics</td>
<td>Membership</td>
<td>Number of days since the user registered on the site</td>
<td>187.01</td>
<td>139.94</td>
</tr>
<tr>
<td></td>
<td>Active Users</td>
<td>Number of active users in month $t$</td>
<td>246.373</td>
<td>72.303</td>
</tr>
<tr>
<td></td>
<td>Total Bounty</td>
<td>All bounties available on the site</td>
<td>131.496</td>
<td>170.813</td>
</tr>
</tbody>
</table>

4. Methodology

StackExchange has specific cut-offs of reputation for users to gain additional privileges. For example, a user can comment on (vote down) others’ posts once her reputation is higher than 50 (125). This structure
enables regression discontinuity to estimate the effect of reputation on user contribution [23]. If gaining additional privileges is the driving force of user contribution, we expect an increase in actions after a user’s reputation passes each threshold. The running variable in our regression discontinuity is reputation, which is obtained only if a user’s questions/answers are voted up by others, i.e., her contribution is recognized as high quality. Hence, reputation cannot be manipulated directly by the user.

We also use a difference-in-difference approach to estimate the effect of relative reputation and rankings. This is to mitigate endogeneity in identifying causal effects (e.g., Zhu and Zhang, 2010). We estimate the contribution of user \( i \) at site \( j \) (\( j = b \) or \( c \)) in month \( t \) as a function of her ranking of reputation and badges in month \( t-1 \):

\[
\text{Contribution}_{it}^b = \beta_0 + \beta_1 \text{Ranking}_{it-1}^b + \beta_2 \text{Badge}_{it-1}^b + \lambda_i^b
\]

\[+ \eta_i + \epsilon_{it}^b \tag{1}\]

\[
\text{Contribution}_{it}^c = \beta_0 + \beta_1 \text{Ranking}_{it-1}^c + \beta_2 \text{Badge}_{it-1}^c + \lambda_i^c
\]

\[+ \eta_i + \epsilon_{it}^c \tag{2}\]

where “Contribution” represents either contribution quantity or quality variables. “Ranking” includes three dummies Top 4, Top 12 and Top 36, “Badges” are Bronze and Silver badges, and \( Z \) controls for site-specific characteristics (Active Users, Total Bounty). The error term \( \lambda_i = \theta_i + \eta_i + \epsilon_{it} \), where \( \theta_i \) is the time-variant user-specific effect constant across sites, \( \eta_i \) is user-site-specific fixed effect, \( \epsilon_{it} \) is the user-site-specific time-variant effect which is assumed to be Normal i.i.d distributed. We take the first difference between (1) and (2) to eliminate user-specific effect:

\[
\Delta \text{Contribution}_{it} = \beta_1 \Delta \text{Ranking}_{it-1}^b + \beta_2 \Delta \text{Badge}_{it-1}^b + \Delta \eta_i + \Delta \epsilon_{it}^b \tag{3}\]

Then we take another difference of (3) over \( t \) and \( t-1 \) to eliminate site-user-specific fixed effect:

\[
\Delta \Delta \text{Contribution}_{it} = \beta_1 \Delta \Delta \text{Ranking}_{it-1} + \beta_2 \Delta \Delta \text{Badge}_{it-1} + \Delta \Delta \epsilon_{it}^b \tag{4}\]

\[+ \Delta \eta_i \]

**5. Estimation and results**

We first use regression discontinuity to estimate the effect of reputations on user contributions around the cutoff of reputation 50 (comment), 100 (edit), and 125 (votedown), respectively. Surprisingly, the results show no evidence of increased activities at each threshold of reputation. For instance, as shown in Figure 2 and Table 2 below, around the small neighborhood of 50 reputation points, none of the activities (question, answer, comment, and total of all activities) seem to increase significantly after crossing the threshold (results of other cutoff points are not reported). Hence, H1 is not supported. This suggests that gaining more privileges may not be the driver of user contribution.

Next, we estimate (4) by difference-in-difference. The results of relative reputation on contribution quantity and quality are reported in Table 3 and Table 4 below, respectively. In terms of virtual rewards, we compare the first columns of the two tables, and see that the bronze badges have a significant effect only on increasing the quality of questions (the coefficient is 0.116 on Bronze for Questions Upvotes, at 5% significance level, in Table 4). It means that earning more bronze badges in the previous month can better motivate higher quality questions. This provides weak evidence for virtual rewards (H2).

As can be seen from Columns 2 and 3 in Table 3, users with Top 4 reputation tend to supply more knowledge (Answers and Comments) significantly in the next period (coefficient is 3.824 and 15.47, respectively). This provides evidence for H3 in the positive direction. The effect of Top 12 users is also significant in providing more answers, although the magnitude is smaller and less significant than the Top 4 users (coefficient is 2.954 at 10% level). This further supports our conjecture that the reputation works through social comparison: if social comparison drives user contributions, then the effects of higher ranking would be stronger than lower rankings. The evidence that top users make more efforts than bottom users contrasts with the findings by Chen et al. (2010). It is possible that top users value their perceived social identity to a greater extent [9].

The coefficient on relative reputation in Column 1, Table 4 shows that the improvement in the quality of questions mainly results from Top 4 users (coefficient is 2.504 at 10% level). Also, Top 4 users tend to provide higher quality answers, measured by both Answers Upvotes and Answers Accepted; the effect is followed by Top 12 and Top 36 (first three coefficients in Columns 2 and 3, Table 4). This provides further evidence for H3 in the positive direction. In addition, the direction of the effect and the pattern of the magnitudes suggest that the quality of answers in the next period increases as a user has higher reputation ranking. This implies that social comparisons can also improve the quality of answers.

While reputation does not directly motivate user contribution, relative reputation (ranking) is found to be the mechanism. An implication follows that the reputation system can be effective, only if it is
implemented in a way that facilitates comparison among users and stimulates their intrinsic motivation.

![Figure 2. Regression Discontinuity: threshold of 50 reputation points](image)

**Table 2. Regression Discontinuity: Effect of Reputation on Contribution Quantity**

<table>
<thead>
<tr>
<th></th>
<th>Total Actions</th>
<th>Questions</th>
<th>Answers</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth</td>
<td>5.83</td>
<td>3.3</td>
<td>3.13</td>
<td>5.6</td>
</tr>
<tr>
<td>Local Wald estimate</td>
<td>0.41</td>
<td>-0.39</td>
<td>-0.33</td>
<td>1.32</td>
</tr>
<tr>
<td>p-value</td>
<td>0.79</td>
<td>0.199</td>
<td>0.38</td>
<td>0.132</td>
</tr>
</tbody>
</table>

**Table 3. Effect of Reputation Ranking and Badges on Contribution Quantity**

<table>
<thead>
<tr>
<th></th>
<th>Questions</th>
<th>Answers</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>L.Top4</td>
<td>0.6409</td>
<td>3.824**</td>
<td>15.47***</td>
</tr>
<tr>
<td>L.Top12</td>
<td>0.365</td>
<td>2.954*</td>
<td>4.891</td>
</tr>
<tr>
<td>L.Top36</td>
<td>-0.004</td>
<td>0.461</td>
<td>0.146</td>
</tr>
<tr>
<td>L.Bronze</td>
<td>0.027</td>
<td>0.058</td>
<td>-0.086</td>
</tr>
<tr>
<td>L.Silver</td>
<td>-0.089</td>
<td>-0.079</td>
<td>-0.376</td>
</tr>
<tr>
<td>Active users</td>
<td>5.6e-05</td>
<td>4.5e-04*</td>
<td>0.001*</td>
</tr>
<tr>
<td>Total Bounty</td>
<td>3.0e-06</td>
<td>-3.7e-05</td>
<td>-8.9e-05</td>
</tr>
<tr>
<td>Constant</td>
<td>0.016</td>
<td>0.091</td>
<td>0.358*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Questions</th>
<th>Answers</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>5558</td>
<td>5558</td>
<td>5558</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.326</td>
<td>0.552</td>
<td>0.747</td>
</tr>
</tbody>
</table>
Note: * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Effect of Reputation Ranking and Badges on Contribution Quality

<table>
<thead>
<tr>
<th></th>
<th>Q Upvotes</th>
<th>A Upvotes</th>
<th>A Accepted</th>
</tr>
</thead>
<tbody>
<tr>
<td>L.Top4</td>
<td>2.504*</td>
<td>2.469***</td>
<td>2.233***</td>
</tr>
<tr>
<td>L.Top12</td>
<td>0.461</td>
<td>2.204***</td>
<td>0.922***</td>
</tr>
<tr>
<td>L.Top36</td>
<td>0.066</td>
<td>0.529*</td>
<td>0.132</td>
</tr>
<tr>
<td>L.Bronze</td>
<td>0.116**</td>
<td>0.038</td>
<td>0.004</td>
</tr>
<tr>
<td>L.Silver</td>
<td>-0.319**</td>
<td>0.047</td>
<td>-0.009</td>
</tr>
<tr>
<td>Active users</td>
<td>7.0e-05</td>
<td>1.8e-04</td>
<td>7.1e-05</td>
</tr>
<tr>
<td>Total Bounty</td>
<td>7.8e-05*</td>
<td>4.5e-05**</td>
<td>3.5e-07</td>
</tr>
<tr>
<td>Constant</td>
<td>0.046</td>
<td>0.055</td>
<td>-5.7e-04</td>
</tr>
</tbody>
</table>

N 5558 5558 5558
R-squared 0.229 0.408 0.602

Note: * p<0.10, ** p<0.05, *** p<0.01.

A possible interpretation is that users with higher rankings may be keener to maintain their reputation and status as knowledge leaders in the community. As these users may also have developed better expertise, they are also more likely to supply high quality knowledge (answers).

6. Conclusion and discussions

Online knowledge communities have the advantage of mobilizing knowledge across boundaries and engaging the wisdom of the crowds. Designing mechanisms to motivate user contribution is important to foster these open collaboration platforms. As many organizations have launched online knowledge platforms to promote knowledge flow and creation, it becomes a significant agenda to understand and manage platform design. Virtual rewards and reputation can be a solution to induce and sustain desired user behavior. In this paper, we use StackExchange.com as an example to investigate the effectiveness of reputation and virtual rewards. We find that unexpectedly, a user’s reputation does not directly lead to more or better contributions in the future. Gaining privilege through earning reputation does not drive user contributions. Instead, reputation plays a role only if it is perceived as a relative measure (rankings). Comparing with others may increase peer pressure, which can motivate one to contribute more and better, and maintain her status in the community. Virtual rewards are also effective to improve the quality of questions, but not as significant as relative reputation. Together, our results suggest that firms should make use of peer effects and facilitate comparison between users when designing reputation system in open communities.

This research makes two-fold contributions to the literature. First, it shows that different motivating mechanisms work differently to motivate different types of user activities. The role of reputation is indirect, contract to the common belief. It is important to utilize peer effect to stimulate user contribution. Second, many of the extant studies on public goods are based on small samples of lab experiments or self-reported cross-sectional surveys (e.g., [25], [26]). Therefore, the results may have limited applicability and generalizability. On the contrary, our study uses a large sample of field data from a representative knowledge community. With these longitudinal observational data, we are able to reveal the specific effects of the motivating mechanisms on contribution behaviors. As such, we contribute to the understanding of the public goods problem beyond the lab environment. We extend the public goods framework to the online community context, and test the effects of different motivating mechanisms. The methodology can be extended to study other knowledge collaboration communities, and more broadly, open platforms where monetary compensation is unavailable.

Furthermore, this study offers insightful managerial implications for community designers of open collaboration. Companies now are leaning more towards communities to manage external innovations. How to manage the community is a significant question, but the answer is largely unknown. By studying the effects of different motivating
mechanisms, we provide guidance for organizations who want to utilize the power of the crowds to accumulate knowledge through open innovation. Community designers can draw from our results to inform their design decisions that influence whether and how people will contribute to a community. For instance, based on our results about social comparison and peer effect, if the designer of the community makes it easier to publicize user rankings in the community, users are more likely to make higher quality contributions. Another example is to carefully choose badge system, depending on the goal of the community. Although badges are widely believed to enhance user contributions, but its effect seems subtle. If the objective is to accumulate greater number of contributions, then the badge system may not help much, but it may be useful if enhancing contribution quality is the goal. Online knowledge communities in the corporate setting may not be identical to what we study here, as users (employees) may not be anonymous and thus have career concern, and companies can utilize monetary incentives, but the general implications are still applicable and relevant.

Overall, our study provides insights into how to effectively motivate contributions on knowledge collaboration communities. It advances the literature on mechanism design of online knowledge communities. In future studies, we will collect more data from other sites on StackExchange (e.g., Superuser.com), and analyze different unit of analysis (e.g., user-daily), so as to further test the robustness of our findings.

7. References


