Spillover Effects of Financial Incentives on Non-Incentivized User Engagement: Evidence from an Online Knowledge Exchange Platform

LINI KUANG, NI HUANG, YILI HONG, AND ZHIJUN YAN

LINI KUANG (kuanglini@hotmail.com) is a Ph.D. candidate in the Department of Management Engineering at School of Management and Economics, Beijing Institute of Technology. Her research interests include user behavior on online community, e-health, and social networks.

NI HUANG (ni.huang@asu.edu) is an Assistant Professor of Information Systems in the Department of Information Systems at the W. P. Carey School of Business, Arizona State University. She obtained her Ph.D. in Business Administration at the Fox School of Business, Temple University. Her expertise concerns IT artifact design on digital platforms, taking the research approaches of natural and field experimentation. Dr. Huang's research has been published in such journals as *Management Science, MIS Quarterly, Journal of the Association for Information Systems*, and *Journal of Consumer Psychology*.

YILI HONG (hong@asu.edu) is an Associate Professor of Information Systems, Co-Director of the Digital Society Initiative, and the Ph.D. Program Director in the Department of Information Systems at the W. P. Carey School of Business, Arizona State University. He received his Ph.D. in Business Administration at the Fox School of Business, Temple University. He is an external research scientist for Freelancer, fits.me, Extole, Yamibuy, Meishi, Picmonic, among others. Dr. Hong's research interests focus on sharing economy, digital platforms, and user-generated content. His research has received several awards and has appeared in *Management Science, Information Systems Research, Journal of Management Information Systems, MIS Quarterly*, and *Journal of the Association for Information Systems*. He is an Associate Editor of *Information Systems Research* and on the editorial board of *Journal of the Association for Information Systems*.

ZHIJUN YAN (yanzhijun@bit.edu.cn; corresponding author) is a Professor in the Department of Management Engineering at School of Management and Economics, Beijing Institute of Technology, China. He received his Ph.D. from that institution. His research interests include electronic commerce, social network analysis, and health

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/mmis.

Journal of Management Information Systems / 2019, Vol. 36, No. 1, pp. 289–320.

ISSN 0742–1222 (print) / ISSN 1557–928X (online)
DOI: https://doi.org/10.1080/07421222.2018.1550564

care management. Dr. Yan has published in *Information & Management, Journal of Electronic Commerce Research*, and *Information Technology & People*, among other journals.

ABSTRACT: Online knowledge exchange platforms have become an important information technology (IT) artifact that empowers online learning for the Internet users. A key challenge for knowledge exchange platforms is how to motivate the desirable user engagement behaviors. Based on the motivation theory and the equity theory, we propose a set of hypotheses regarding the spillover effects of financial incentives on three types of desirable yet non-incentivized user engagement, namely, voluntary knowledge sharing, knowledge seeking, and social engagement. We obtain an archival data set from a major online knowledge exchange platform (Zhihu.com) to evaluate our hypotheses. Leveraging a quasi-natural experiment wherein the platform implemented a paid knowledge sharing feature, we employ difference-in-differences models in tandem with propensity score matching to evaluate the spillover effects of financial incentives on the abovementioned types of engagements. Our results show that the initial financial incentives on the paid knowledge sharing activities further motivate users to voluntarily share more knowledge and increase their social engagement in the platform. However, the financial incentives have no significant impact on users' knowledge seeking behavior. Our study suggests that the financial incentives not just have an effect on incentivized engagement, but they spillover to users' desirable non-incentivized online engagement behaviors. Therefore, the overall positive effect of financial incentives to a platform is likely under-estimated in prior research. Our research offers implications to practice that financial incentives can be an effective strategy to nurture users, to seed content, and to enhance sociality of a platform.

KEY WORDS AND PHRASES: financial incentives, spillover effect, user engagement, knowledge sharing, knowledge seeking, social engagement, online platforms, user motivation.

Introduction

In recent years, online knowledge exchange platforms such as Quora.com, StackOverflow.com, and Zhihu.com have gained widespread popularity and rapidly evolved into individuals' go-to places for obtaining and sharing knowledge [17]. These platforms have attracted millions of users and have become valuable information technology (IT) artifacts for knowledge accruement and online learning that are available to the public for free. In the online knowledge exchange platforms, individuals can simultaneously share their knowledge, experience, and expertise by answering questions and posting articles. The knowledge sharing behavior, in turn, offers these individuals a sense of satisfaction for assisting other users [21] and potential social and economic returns [19]. In addition to their knowledge seeking and sharing activities, users in the online knowledge exchange platforms may also engage in social activities with individuals who share similar interests. Therefore, online knowledge exchange platforms serve the purpose of not only knowledge repositories but also social engagement.

The sustained development of online knowledge exchange platforms depends on the users' active engagement within the platforms, particularly, knowledge sharing, knowledge seeking, and social engagement. However, similar to other platforms that rely on user-generated knowledge and content, such as online reviews [5, 11], online crowdsourcing [21], and prediction markets [34], knowledge exchange platforms face the under-provision problem, wherein users lack the motivation to actively engage with the platform, such as knowledge sharing. The users' lack of active engagement is also related to the aspect of knowledge seeking behavior because a large fraction of users churn from the knowledge exchange platforms after only one post [50]. The users' knowledge seeking behaviors (e.g., posting questions) are crucial to the health of knowledge exchange platforms because thought-provoking questions can trigger other users' knowledge sharing behaviors. Furthermore, users' social engagement plays a critical role in their affinity with the online communities, an aspect that is crucial to a community's sustained success [37]. Therefore, to improve user engagement, online knowledge exchange platforms typically set up various motivation measures, such as providing virtual points and setting membership levels based on users' engagement behavior [17, 26]. Alternately, these platforms provide users with financial rewards to stimulate engagement [20, 22, 35].[1]

The current study analyzes the impact of financial incentives on the users' engagement behaviors in a hybrid knowledge exchange platform, where paid and voluntary knowledge exchange services coexist [7, 25]. We leverage a quasi-natural experiment wherein the platform first implemented incentive-based paid knowledge exchange services. After the users received financial incentives for knowledge sharing activities, we investigate how the financial incentives insert spillover influences on the users' non-incentivized engagement behaviors, such as voluntary knowledge sharing, knowledge seeking, and social engagement. We find interesting spillover effects of financial incentives on the non-incentivized user engagement behavior in the knowledge exchange platform. Our results show that the financial incentives initially received by users for knowledge sharing activities have broad spillover effects on the other related non-incentivized engagement behaviors. Specifically, the financial incentives largely increase voluntary knowledge sharing and social interactions, yet have no significant effect on users' knowledge seeking behavior. In addition, the amount of financial rewards plays the role of an important moderator, such that high financial rewards have a stronger effect on users' non-incentivized engagement behaviors than low financial rewards. In summary, our analysis provides novel findings on the existence of the spillover effects of financial incentives on non-incentivized engagement behaviors in online knowledge exchange platforms.

Our study makes several important contributions to the related literature on financial incentives, knowledge contribution, and more broadly, user engagement. To begin with, prior research on online knowledge exchange platforms mostly focused on the motivations for knowledge sharing behaviors [8, 22, 35], while overlooking knowledge seeking and social behaviors that also play important roles in the sustainable development of knowledge exchange platforms. For example, Khansa et al. [26] suggested that knowledge seeking is an important type of user behavior. In the majority of prior studies, users in knowledge exchange platforms are regarded as either knowledge seekers or knowledge contributors. In fact, users normally play multiple roles in knowledge exchange platforms. A user can be a knowledge seeker, a contributor, or a friend of other users in such platforms. Extending prior work along the line, the current study considers the different aspects of platform engagement in a comprehensive manner.

Additionally, previous work has examined financial incentives as an important motivating factor for the desired individual behaviors [15, 20]. For instance, Hsieh et al. [20] found that high compensation may elicit more and longer answers but not necessarily high-quality answers. In contrast, Gneezy and Rustichini [15] suggested that high school students invest more efforts in volunteering when they are not paid than when they are paid a small amount of financial incentive for their work. Thus, prior research appears to suggest that individuals commonly have a payment threshold for their motivation. If individuals receive financial incentive exceeding the threshold value, the incentive might have a positive effect on the targeted behaviors; while low payment below the threshold value might not produce similar effects. Accordingly, while not the focus of this study, we also report some exploratory findings on the role of the amount of financial incentives on users' engagement behaviors in knowledge exchange platforms.

Moreover, above and beyond prior work that examines the direct effect of financial incentives on paid knowledge contribution, the current study focuses on the spillover effects of financial incentives on non-incentivized engagement behaviors. Although many studies investigated the effects of financial incentives on the directly incentivized activities of users in online platforms, rarely has prior work considered the spillover effects of financial incentives on non-incentivized user engagement behaviors [29]. Investigating the spillover effects of financial incentives on related non-incentivized engagement behaviors is important for the sustained development of knowledge exchange platforms. If the financial incentives targeted at one behavior have certain unintended negative effects on other related behaviors in knowledge exchange platforms, such as decreasing users' voluntary knowledge sharing or social activities, this approach may be detrimental to the overall development of the platforms. Therefore, understanding the spillover effects of financial incentives could offer valuable design implications for online knowledge exchange platforms.

The rest of the paper is organized as follows. In the following sections, we review the related work, introduce the motivation theory and the equity theory as our theoretical foundation, and develop our research hypotheses. We then describe the research context and report the details of our data, followed by the econometric model and corresponding estimation results. Finally, we conclude with a discussion of the implications of our findings to research and practice.

Related Literature

User Engagement in Online Platforms

The majority of prior literature on user engagement in online platforms focused on content contribution or knowledge sharing behaviors, which comprise an important stream of IS literature on knowledge management [9, 32, 53]. Drawing on theories of goal-oriented actions, Khansa et al. [26] suggested that users' active knowledge sharing behaviors are largely driven by non-monetary factors, such as membership level, length of tenure, and habitual behaviors. Such effects are also highly heterogeneous across gender [6]. Researchers also found that financial incentives influence knowledge contribution behaviors. For example, Chen et al. [7] and Hsieh et al. [20] found that a high asker-posted price of questions could motivate answerers to spend extra time on the questions, whereas the amount of financial incentive has no effect on the answer quality. Furthermore, Zhao et al. [52] found that the extrinsic rewards motivate inactive users yet demotivate active users. In addition to user characteristics and incentives, users' network positions in the platform [51] and the knowledge validation process [12] are also found to affect knowledge sharing and contribution.

Another stream of related literature evolves around knowledge seeking behaviors. Ruth [40] divided the askers in knowledge exchange platforms into two groups based on their asking behaviors, namely, one-time askers and continuing askers. Drawing on satisfaction theory, Ruth [40] studied how the price, response time of answerers, and comments influence askers' satisfaction and users' continuing asking behaviors. Habitual factors and current membership status were also found to affect users' continuing asking behaviors [26]. Using a dataset from a pay-for-answer site, Hsieh et al. [20] found that askers tend to pay for factual questions and pay extra for tough questions. The characteristics of knowledge seekers also affect the quality of exchanged knowledge [3]. When a knowledge seeker discloses more individual characteristics, the knowledge contributor will place more trust in the knowledge seeker, thus increasing the perceived quality of exchanged knowledge.

Social engagement is also considered an important driver for users' satisfaction and continued engagement in knowledge exchange platforms [40]. Raban [36] performed a content analysis and found that social interactions between askers and answerers in knowledge exchange platforms can catalyze economic activity, further leading to increased information value [40]. Establishing new social ties is also a kind of important social interaction behavior that can affect users' content generation behaviors [42]. However, a majority of the prior literature considers the users in knowledge exchange platforms as either askers or answerers. Consequently, previous work mostly studied either the knowledge seeking behaviors of askers or the knowledge sharing behaviors of answerers in isolation. In the current work, we consider the multiple roles of the users. We not only study users' knowledge sharing behavior, but their knowledge seeking and social behaviors as well. Our study aims at extending prior research on user engagement in knowledge exchange platforms by considering the multiple aspects of user engagement with a comprehensive study framework, namely, voluntary knowledge sharing, knowledge seeking, and social engagement.

Financial Incentives

Financial incentives are being extensively used by policymakers and managers to induce desired behaviors [44]. Economic theory holds that individuals are rational and constantly pursue their maximum interest. Existing literature on the effectiveness of financial incentives has analyzed the performance of targeted behaviors that are objectives of financial incentives. Overall, financial incentives are found to influence individuals' incentivized behaviors [5, 28, 42]. For example, in the offline context, financial incentives have been proven to motivate healthy behaviors [1, 39, 45]. In the online community, financial incentives also serve as a marketing tool to stimulate desired behaviors. For example, financial incentives are considered an effective incentive to improve user engagement in online communities. For example, in open source software (OSS) communities, developers who are paid to join in OSS activities participate more compared with their unpaid counterparts [38]. In electronic commerce platforms, offering financial incentives to consumers can stimulate users to write additional online reviews [5]. In knowledge exchange platforms, when questions are difficult to solve, askers may pay financial rewards as motivation for other users to provide high-quality answers. In addition, high financial rewards can elicit more and longer answers than low monetary ones [20].

Some contradictory findings regarding financial incentives have also been reported. For example, Garnefeld et al. [14] found that financial incentives can increase the short-term engagement behaviors of users; however, in the long run, the financial incentives are likely to decrease users' intentions to engage in an online community. On the contrary, Sun et al. [43] found that after financial rewards for posting reviews are introduced, the reviews contributed decreased, in particular for those who are highly connected in the community. Gneezy et al. [16] offered a clear picture as to when and why financial incentives do or do not work. They concluded that financial incentives have two kinds of effects: the standard direct price effect that incentivizes desired behaviors and an indirect psychological effect. In certain cases, the direction of the psychological effect is opposite to that of the price effect, and the psychological effect can crowd out desired behaviors. The effectiveness of financial incentives depends on the kind of targeted behavior and the amount of financial incentives [16].

There is a scarcity of research on the effectiveness of financial incentives on related non-incentivized behaviors in the online context. Findings from the offline context suggested that interventions based on financial incentives can both improve target behaviors and affect the treated group's related behaviors, supporting the existence of the spillover effects of offline financial incentive-based intervention [29]. However, owing to the relatively anonymous nature of the online platforms, users may not change their related behaviors when they receive financial rewards. Therefore, our study aims to investigate the spillover effects of financial incentive-based programs in online knowledge exchange platforms.

Theoretical Foundation and Hypothesis Development

Motivation Theory

Motivation theory has been widely used to explain users' online engagement behaviors [22, 31, 38]. The motivation theory distinguishes two types of motivations, namely, intrinsic and extrinsic motivations [10, 41]. Intrinsic motivations refer to the inherent desire to do something because of the inherent satisfaction or enjoyment of the action itself. In contrast, extrinsic motivation means that an act is performed because of existing external incentives [17], and not because of the satisfaction of performing the action. Research on the motivation theory has suggested that intrinsic motivation depends on the perceived sense of autonomy. If users engage in an activity because of the external value rather than the enjoyment of the activity itself, then their perceived self-determination will be undermined. Thus, extrinsic incentives will crowd out intrinsic motivations if the former are considered dominating. However, if extrinsic incentives can conduce to individuals feeling competent without losing their perceived self-determination, then extrinsic motivation will enable the individuals to experience enhanced intrinsic motivation for performing an activity. As a result, extrinsic incentives will crowd in intrinsic motivations if the former are perceived as acknowledging [31, 41].

Our study context—a hybrid knowledge exchange platform—offers a rich context to examine the users' multiple motivations and behaviors. On the one hand, users can voluntarily contribute knowledge, seek knowledge for free, and form social relationships with other peer users in knowledge exchange platforms because of their intrinsic motivation, which in turn can satisfy their needs for competence, control, and autonomy [10, 41]. These engagement activities allow users to experience a sense of achievement in assisting others, self-worth, and belongingness. When users participate in voluntary activities, such as voluntary knowledge sharing in the platform, the lack of financial rewards retain the intrinsic motivation and possibly even enhance the intrinsic motivation. On the other hand, a hybrid knowledge exchange platform provides users with extrinsic motivation, such as financial rewards for certain kinds of behaviors. In our case, users are remunerated for knowledge sharing behaviors. Given that the financial rewards are not directly aimed at the voluntary engagement behaviors, the users could still voluntarily contribute knowledge in hybrid knowledge exchange platforms without losing autonomy. More importantly, financial rewards can also be regarded as recognition of competence. In other words, financial rewards received from paid activities allow users to satisfy their needs for autonomy and competence when they participate in voluntary activities. Consequently, the financial rewards not only provide extrinsic motivation, but also enhance the intrinsic motivation under this condition [10, 41]. Drawing on the motivation theory, we expect that the users will participate in other voluntary activities driven by intrinsic motivation after they receive financial rewards from paid engagement activities.

Equity Theory

Equity theory suggests that individuals will work to restore equity if they sense that they will be under-rewarded or over-rewarded in an exchange [24]. When individuals manage their relationships with others, they assess the ratio of their outputs and inputs to the relationships [24]. If they perceive that the input-output ratio is not equal, similar to an exchange, they will make efforts to restore equity [2]. After the launch of the fee-based knowledge sharing feature, our study context evolved from a purely community-based knowledge exchange platform to a hybrid knowledge exchange platform. The output of knowledge exchange activity in the platform also changed accordingly. With the fee-based feature, users receive an extra amount of financial reward for participating in paid knowledge exchange activities. The extra financial rewards that the users received from the websites might lead to a feeling of indebtedness to the knowledge exchange platforms. To strive for equity, the feeling of indebtedness could motivate the users to increase their input to the platform, such as reciprocating the site by voluntarily contributing more knowledge. Reciprocal behavior could also help users avoid being considered as individuals who only focus on their self-interest [13]. Therefore, considering the equity theory, we expect that financial rewards might have a positive spillover effect on the users' reciprocity, such as voluntary knowledge sharing, knowledge seeking, and social engagement.

Voluntary Knowledge Sharing

In knowledge exchange platforms, the voluntary knowledge sharing behaviors normally include voluntary answering behaviors and voluntary article-posting behaviors. For voluntary answering, users answer other users' questions without any financial rewards. Users often voluntarily participate in voluntary answering behaviors. At the same time, users can post original articles on a voluntary basis in the knowledge exchange platforms. These articles generally provide a detailed explanation of specific themes and topics under the users' expertise.

The paid and voluntary knowledge sharing activities are commonly seen as complementary activities for the users in a knowledge exchange platform. To begin with, the voluntary activities can significantly improve users' satisfaction and continuance, which become an integral part of a fee-based service market [40]. The involvement of answerers in voluntary knowledge sharing activities helps establish a positive online image of being altruistic and benevolent. In turn, the positive online image of voluntary answerers strengthens the influence of the answerers' paid knowledge sharing activities and inspires askers to join the paid knowledge sharing activities accordingly. Considering that financial incentives have a positive effect on paid knowledge sharing activities, these incentives may lead to an increase in voluntary knowledge sharing activities.

At the same time, financial rewards received from participating in paid knowledge sharing activities represent the recognition of personal competence, which can enhance the intrinsic motivations of users. When users receive financial rewards from knowledge sharing, they also experience self-confidence in their expertise in specific topics. The increased self-efficacy might also drive users' intrinsic motivation for voluntary knowledge sharing behaviors. Taken together, it is plausible that the financial incentives might enhance the users' intrinsic motivation and further inspires them to engage in voluntary knowledge sharing activities.

Therefore, based on the motivation theory, users tend to engage in more voluntary knowledge sharing activities in the knowledge exchange platform when they receive financial rewards. In addition, according to the equity theory, when users receive financial rewards from the knowledge exchange platform, they voluntarily contribute extra time and effort to the knowledge exchange platform to avoid being perceived as purely driven by financial incentives by establishing a well-regarded image [7, 27]. Bearing the above arguments in mind, users tend to reciprocate the platform by involving in more voluntary knowledge sharing activities. Formally, we hypothesize the following:

> *Hypothesis 1: Users will increase their voluntary knowledge sharing activities if they receive financial rewards from paid knowledge sharing activities, including voluntary answering (H1a), and voluntary article posting (H1b).*

Knowledge Seeking

In knowledge exchange platforms, the knowledge seeking behaviors generally refer to posting questions to obtain other users' answers. In posting questions on knowledge exchange platform, the user seeks help in certain topics; therefore, knowledge seeking may indicate that the users lack knowledge in those topics. In most knowledge exchange platforms, users are allowed to post questions voluntarily (i.e., without monetary costs). However, knowledge seeking behaviors can impose other non-monetary costs, such as psychological costs. Given posting questions is naturally a kind of help-seeking behavior, prior literature suggested that asking for help can reduce users' personal sense of self-competence and impede their social status in knowledge exchange platforms [20, 48]. When users receive financial rewards from participating in paid knowledge sharing activities, their expected audience size and rewards amount are related to their perceived ability. As users are typically loss averse, to maintain their knowledgeable image, users who receive financial rewards are demotivated to seek knowledge in the knowledge exchange platforms compared to those who do not receive financial rewards. Therefore, financial incentives are likely to decrease paid users' knowledge seeking behaviors. We hypothesize the following:

> *Hypothesis 2 (H2): Users will decrease their knowledge seeking activities in knowledge exchange platforms if they receive financial rewards from paid knowledge sharing activities.*

Social Engagement

Social engagement among users is a key feature of online platforms that rely on user content generation [43], and it is vital for the sustained development of content-based online platform [33]. In a typical knowledge exchange platform, such as Zhihu and Quora, users can follow and be followed by other users. Typically, the key activities of the user being followed will be pushed to the follower. In what follows, we conceptualize the spillover effects of financial incentives on users' social engagement, measured by the number of new followers and followees each month.

On the one hand, the financial rewards received from the sites allow the users to experience a high level of satisfaction by enhancing users' loyalty [4] and their perception of self-efficacy [22], which are important intrinsic motivations. The enhancement of intrinsic motivation can increase users' social interactions in the community [8].

On the other hand, paid knowledge sharing activities can increase the users' number of followers. The initiation of paid knowledge sharing activities serves as a quality signal of the users, indicating that they are likely experts in a specific topic. Thus, users on the platform will attempt to establish social connections with those who have initiated paid knowledge sharing activities. Furthermore, paid knowledge sharing activities can increase exposure for users, increasing their reach to more users who will potentially follow them on the platform. Therefore, we hypothesize the following:

> *Hypothesis 3: Users will increase their social interactions in knowledge exchange platforms if they receive financial rewards from paid knowledge sharing activities, including following more users (H3a), and being followed by more users (H3b).*

Research Context and Data

Research Context

Our research context is a popular online knowledge exchange platform in China, *Zhihu.com*, wherein platform users ask questions, answer questions, post articles, and build social connections. As of March 2017, approximately 70 million users have registered on the platform. Our natural experiment occurs on May 16, 2016, in which this platform rolled out a new feature called "Live."[2] A Live session is a paid, real-time, and online question-and-answer service. Hosting a Live session means that users create a communication group to share their knowledge at a specified time and set up the entry costs of the group. Other users can participate in the communication group by paying entry costs to the Live session holder. In the communication group, the Live session holder will answer the paying audiences' questions in real time. A Live session lasts for two hours. When a Live session ends, the Live holder can no longer answer the audience's questions in the communication group.

We consider *Zhihu.com* an ideal setting for our study for several reasons. First, the site is among the largest knowledge exchange platforms in China. It has brought together nearly 70 million users from the Internet and covers diverse fields such as technology, business, psychology, and culture, resulting in 15 million questions asked, 55 million answers given, and 250,000 topics discussed. Given the popularity of the site, any functional change in the site will have an important influence. Second, the utmost advantage of our research context is the occurrence of natural experiment with the change in the platform's Live feature. The platform was initially a completely social market without economic rewards for knowledge contributors. However, it has developed into a mixed social and economic market after the monetary-incentive-based feature was introduced. This setting allowed us to study the change in engagement behaviors of participants. Given that not every user participates in the economic activity, we can consider the nonparticipants as the control group users in this study. Third, as a knowledge exchange platform, *Zhihu.com* is both a knowledge sharing community and a social community. Users can follow (or be followed by) other users with the same interest on certain topics as them. The social property of the platform enables us to study users' social interactions.

Keeping in mind of a quasi-experimental design, we collect data on contribution activities from the knowledge exchange platform from January 17, 2016 to September 17, 2016. The new Live feature, comprises a natural shock in our eight-month sampling window and has the exogenous effect of introducing financial incentives in the site (i.e., treatment). We define the period from January 17, 2016 to the launch time of Live as the pretreatment stage and the period from the launch time of Live to September 17, 2016 as the post-treatment stage. We focus on the users who have held a Live session and registered on the website before the start date of the sampling. The number of users in this treated group during this period was 203. In addition, we randomly select 4,988 users who have not held any Live session within the study period and registered on the site before January 17, 2016. We use these samples as the control group. Figure 1 illustrates the experimental timeline.

To provide more contextual background for readers who have not used Zhihu, Zhihu is similar to Quora. In both Zhihu and Quora, users can ask questions, provide answers, post articles, and establish social ties with other users. A key difference between Zhihu and Quora is that users in Quora will not receive any monetary reward when they share their knowledge with others. In contrast, after the Live session feature implementation, users in Zhihu can choose to participate in both voluntary knowledge sharing activity and monetary reward-based knowledge sharing activities. It is notable that although the feature release was exogenous, the platform users decide whether they will hold a paid Live session. During the

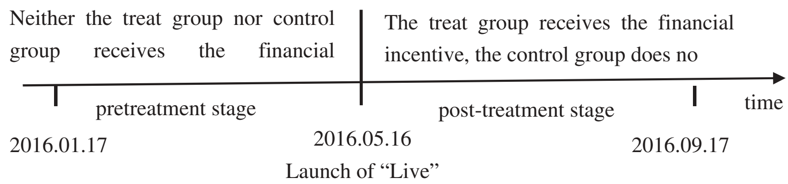


Figure 1. Experimental Timeline.

observational window of our study, each Live session lasts for about an hour, and the Zhihu platform did not charge any commission from Live session holders.

Here, we provide two screenshots of a Zhihu's regular voluntary Q&A discussion and a Live session, in Figures 2 and 3, respectively. Accompanying each original screenshot, we also provide the appropriate translations to the right of the figures.

Dependent Variables

We measure the voluntary knowledge sharing behaviors using two variables: $Answers_{it}$ and $Articles_{it}$. $Answers_{it}$ refers to the number of user i's answers shared on a voluntary basis in month t. $Articles_{it}$ refers to the number of user i's articles shared on a voluntary basis in month t. The voluntary knowledge seeking behaviors is measured using one variable Ask_{it}, which refers to the number of user i's questions asked in month t. We

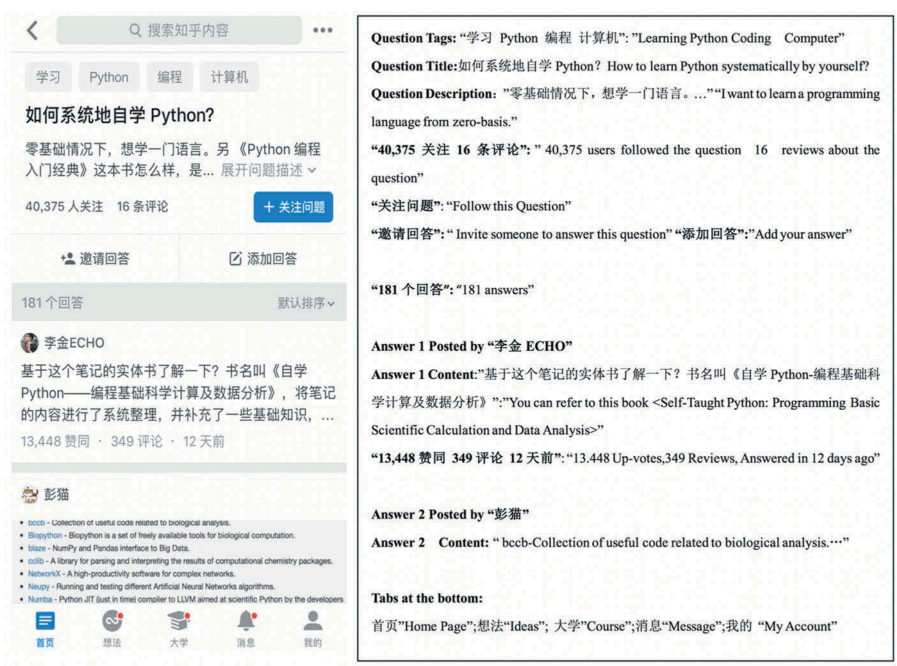


Figure 2. A Screenshot of Voluntary Q&A Discussion (Zhihu) with Translation.

Figure 3. A Screenshot of a Live Q&A Discussion (Zhihu) with Translation.

measure the social behaviors using two variables: $Follower_{it}$ and $Followee_{it}$. $Follower_{it}$ refers to the number of user *i*'s new followers in month *t*. $Followee_{it}$ refers to the number of user *i*'s new followees in month *t*.

Independent Variables

We are interested in how users change their engagement behaviors before and after receiving financial rewards from the paid knowledge sharing activities compared with users who are not receiving financial rewards. Therefore, our focal independent variables are $TreatGroup_i$ and $PostTreatment_{it}$. If user i has ever held a Live session during our study period, the $TreatGroup_i$ variable equals 1, which means the user is a Live holder; otherwise, 0. The $PostTreatment_{it}$ variable equals 1 if month *t* is on or after May 16, 2016.

Control Variables

Social recognition affects users' engagement behaviors [46]. Thus, we also control for the social recognition effect. The cumulative number of favorites and up-votes from other users in the last time period are adopted to measure the social recognition effect. In addition, considering the skewed distribution of the two control variables, we use the log-transformed control variables ($logFav_{it-1}$, $logUpvote_{it-1}$) in our regression model.

We compute the means and the mean differences in the outcome variables for treated and control groups during two periods, namely, before and after launching the economic feature Live. The numbers of treated and control group users are 203 and 4,988, respectively. We collect data for eight months. The total numbers of observations are 1,624 and 39,904 for the treated and control group users (see results in Table 1). The average monthly number of engagement behaviors is higher for treated users than for control group users in both periods. Except for answering behaviors, the engagement behaviors of treated users largely increased after the paid feature was launched. Conversely, the engagement behaviors of control group users remained at roughly the same level over time. Consequently, the differences in engagement behaviors, except for answering behavior, between the two groups widened over time. These model-free results suggested that the treated users who received financial incentives are likely to participate in the kinds of activities in the site relative to the control users. The trends of engagement behaviors between the treated and control groups before Live was launched are roughly consistent, except in Month 2. This finding is attributed to the fact that Month 2 is the time period from January 16, 2016, to February 16, 2016, which covered the Spring Festival holiday, which meant users had extra time to participate in online activities. To minimize the effects caused by the Spring Festival holiday on users' online engagement behaviors [30], we report the results without the data from Month 2.

Table 1. Mean Comparisons of Dependent Variables Between Treated and Control Users

		Treated Users		Control Users		
Variable	Period	Obs	Mean	Obs	Mean	Differences
$Answers_{it}$	Before Launching Live	812	4.341	19,952	1.394	2.947
	After Launching Live	812	3.889	19,952	1.318	2.571
$Articles_{it}$	Before Launching Live	812	1.323	19,952	0.087	1.236
	After Launching Live	812	2.124	19,952	0.114	2.011
Ask_{it}	Before Launching Live	812	0.110	19,952	0.076	0.033
	After Launching Live	812	0.127	19,952	0.064	0.062
$Follower_{it}$	Before Launching Live	812	1819.809	19,952	40.824	1778.985
	After Launching Live	812	2010.216	19,952	41.468	1968.748
$Followee_{it}$	Before Launching Live	812	4.853	19,952	2.819	2.034
	After Launching Live	812	6.117	19,952	3.048	3.069

Empirical Analysis

Spillover Effects of Financial Incentives on Non-incentivized Engagement Behaviors

We adopt the regression framework to detect the shift in engagement behaviors of Live session holders relative to that of non-Live session holders. We rely on a difference-in-differences (DID) approach. The panel data DID regression framework allows us to take advantage of panel data to control for both time-specific and user-specific effects [30]. Our estimating equation for members i in stage t is represented in Equation (1):

$$\begin{aligned} y_{it} = \beta_0 + \beta_1 * TreatmentGroup_i * PostTreatment_t + \beta_2 * logFav_{t-1} + \beta_3 \\ * logUpvote_{t-1} + \sum MonthDummy_t + \alpha_i + \epsilon_{it} \end{aligned} \tag{1}$$

where y_{it} refers to $Answers_{it}$, $Articles_{it}$, Ask_{it}, $Follower_{it}$, and $Followee_{it}$, respectively. The outcome variables in our model are log-transformed to produce an elasticity interpretation. $TreatGroup_i$ is denoted as 1 if a member has ever held a Live session within the study period, and 0 if otherwise. We define the dummy variable $PostTreatment_{it}$ as 1 if month t is on or after May 16, 2016, and 0 otherwise. The coefficient β_1 of the interaction term $TreatGroup_i \times PostTreatment_{it}$ assesses how the contribution behaviors in the treated group change after the financial incentive feature was launched in contrast to that of the control group during the same period. The control variables $logFav_{it-1}$ and $logUpvote_{it-1}$ refer to the cumulative number of favorites and up-votes received from other users in the last time period t-1, respectively. We include dummy variables for each month from February 2016 to September 2016 to control for time-specific effects.

Two challenges are identified in our specification. First, given that the treated users who receive financial incentives are not randomly selected by our researchers, the treated users may have a high propensity to participate in the economic incentive-based activity owing to a few unobserved factors. The unobserved factors will lead to a biased estimation. To address this potential endogeneity problem, we introduce individual-level fixed effects to control for time-invariant, unobserved user characteristics. We also include month dummy variables to control for time-specific effects. Individual-specific effects are determined via F-test and LM test. The Results from the Hausman test also indicate that the fixed-effects model is more appropriate than the random effect model. We present both the fixed-effects model and the pooled ordinary least squares (OLS) model in the Results section.

Second, a few users may change their existing behaviors to increase their popularity and thus attract more audiences to attend the Live sessions that they hold. Hence, the financial incentive-based feature may exert influences before the users actually receive financial rewards. If we use the individual holding dates as the cut-off dates, then our analysis will underestimate the effects of the financial incentive-based feature. Thus, to minimize the biased effect, we use May 16, 2016 as the cut-off rather than dates the users individually held their Live sessions as the cut-off dates. We still use the individual holding dates to report the results in our main analysis. In the following robustness section, we only report the results using May 16, 2016 as the cut-off date. In our regression, when we use May 16, 2016 as the cut-off date, $PostTreatment_{it}$ is 1 if the user i has previously held a Live session and month t is on or after May 16, 2016, and 0 otherwise. When we use individual Live holding dates as the cut-off dates, we redefine that $PostTreatment_{it}$ is 1 if the user i has previously held a Live session in month t, and 0 otherwise.

Columns (1), (3), (5), (7), and (9) of Panel A in Table 2 present the results with fixed effect (FE) using May 16, 2016 as the cut-off date. The variable $TreatGroup_i$ drops from the regression because its value does not vary with time. Column (1) in Table 2 presents the spillover effects of financial incentives on the voluntary contribution of answers each month. Column (3) shows the spillover effects of financial incentives on posting articles on a voluntary basis. Column (5) shows the spillover effects of financial incentives on knowledge seeking behaviors. Columns (7) and (9) demonstrate the effect of financial incentives of paid knowledge exchange on social activities. The coefficient of the interaction term $TreatGroup_i \times PostTreatment_{it}$ of Column (1) is insignificant. Overall, the number of contributing answers did not change after the users received financial incentives. The results fail to support H1a. For the voluntary article posting activity, Column (3) shows that the average number of articles per month increased by 32.0% after users received financial rewards. The result supports H1b. Overall, financial incentives received from paid knowledge sharing behaviors have a positive spillover effects on users' voluntary knowledge sharing behaviors. The coefficient of the interaction term $TreatGroup_i \times PostTreatment_{it}$ of Column (5) is insignificant. Overall, users' knowledge seeking behaviors did not change after the users received financial incentives. The result does not lend support for H2. For social activities, Columns (7) and (9) respectively show that the number of new followers increased by 29.7%, and the number of new followees increased by 16.6% after financial rewards were received for the paid knowledge exchange activity. These results support H3a and H3b. Columns (2), (4), (6), (8), and (10) report the results based on OLS regression, results that are similar to those with the fixed-effects model. Panel B of Table 2 shows the analysis using Live holding dates as the cut-off date for all treated users. In the rest of the analysis, we use Live launching time as the cut-off date.

Robustness Checks

Ruling Out the Holiday Effects

As mentioned in the data description section, our study period includes an important Chinese festival holiday, which may have affected the users' online engagement behaviors. Thus, we exclude this time period and repeat the DID analysis. Table 3 presents the estimation results without the data from Month 2. After the festival effect is excluded, the results support H1a, H1b, H3a, and H3b. The coefficient of the interaction term $TreatGroup_i \times PostTreatment_{it}$ of Column (5) is still insignificant. Hence, again, the result does not lend support for H2.

Table 2. Spillover Effects of Financial Incentives on User Engagement

DV:	$Answer_{it}$		$Article_{it}$		Ask_{it}		$Follower_{it}$		$Followee_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Live Feature Release as the Shock										
TreatGroup$_i$	–	0.140**	–	0.349***	–	(0.013)	–	2.656***	–	0.163**
		(0.065)		(0.045)		(0.012)		(0.084)		(0.066)
TreatGroup$_i$	0.067	0.033	0.320***	0.316***	0.010	0.007	0.297***	0.243***	0.166***	0.152***
xPostTreatment$_{it}$	(0.042)	(0.042)	(0.030)	(0.030)	(0.011)	(0.011)	(0.057)	(0.055)	(0.045)	(0.045)
logFav$_{it-1}$	–0.004	0.007	0.004	0.001***	–0.003	0.001	0.039**	0.373***	–0.032*	0.006
	(0.013)	(0.005)	(0.003)	(0.002)	(0.003)	(0.001)	(0.017)	(0.012)	(0.017)	(0.008)
logUpvote $_{it-1}$	–0.054***	0.119***	0.004*	0.018***	0.000	0.011***	0.143***	0.263***	0.020	0.072***
	(0.018)	(0.006)	(0.003)	(0.002)	(0.005)	(0.001)	(0.026)	(0.011)	(0.021)	(0.007)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,528	41,528	41,528	41,528	41,528	41,528	41,528	41,528	41,528	41,528
R-squared	0.009	0.123	0.042	0.2	0.001	0.014	0.039	0.614	0.009	0.036
# of users	5,191		5,191		5,191		5,191		5,191	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS
Panel B: First Live Event as the Shock										
TreatGroup$_i$	–	0.181***	–	0.393***	–	-0.010	–	2.615***	–	0.210***
		(0.063)		(0.045)		(0.012)		(0.082)		(0.066)
TreatGroup$_i$	0.043	-0.083	0.423***	0.387***	0.013	0.004	0.488***	0.551***	0.180***	0.098
xPostTreatment$_{it}$	(0.041)	(0.052)	(0.033)	(0.041)	(0.012)	(0.014)	(0.069)	(0.069)	(0.054)	(0.064)
logFav$_{it-1}$	–0.004	0.007	0.004	0.009***	-0.004	0.001	0.0383**	0.373***	-0.0323*	0.006
	(0.013)	(0.005)	(0.003)	(0.002)	(0.003)	(0.001)	(0.017)	(0.012)	(0.017)	(0.008)
logUpvote $_{it-1}$	–0.053***	0.119***	0.005*	0.018***	0.000	0.0114***	0.142***	0.262***	0.020	0.072***
	(0.018)	(0.006)	(0.003)	(0.002)	(0.005)	(0.001)	(0.026)	(0.011)	(0.021)	(0.007)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,528	41,528	41,528	41,528	41,528	41,528	41,528	41,528	41,528	41,528
R-squared	0.009	0.124	0.054	0.203	0.001	0.014	0.042	0.615	0.009	0.036
# of users	5,191		5,191		5,191		5,191		5,191	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS

Notes: Clustered-robust standard errors (clustered on users) are reported in parentheses. ***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

Assessing the Self-Selection Problem

Owing to the self-selection problem, we cannot plausibly conclude that the different post-treatment behaviors between the treated and control groups are caused by the "Live" financial incentive feature. The Live session holders generally have greater incentive motivation and are more likely to share additional knowledge and build more social ties in the website than the non-holders over time. Therefore, regardless of whether the financial incentive exists, the members belonging to the treated group appear to contribute further and build more social ties on the website.

To reduce the potential differences between the treated and control groups, we rely on propensity score matching to identify members within the control group with a great level of similarity to members in the treated group in terms of observed characteristics.

We employ a propensity score-matching method for our analyses to balance the observed characteristics between the treated and control groups. We calculate the propensity score using logit regression with an indicator of being treated by the financial incentive as the dichotomous outcome and a set of observed characteristics as covariates (including gender, the total amount of answers, questions, articles contributed by members in the website before May 16, 2016, the total amount of up-votes and favorites that users received before May 16, the total number of followers, and the number of individuals that the user followed before May 16). Then, based on the propensity score, we match members between the treated and control groups by applying two matching methods, the one-to-one nearest neighbor matching without replacement with a caliber of 0.03 and the nearest four neighbors with replacement with the caliber 0.03 matching.

Table 4 presents the summary statistics of the treated and control groups before and after matching using one-to-one nearest neighbor matching without replacement with a caliber of 0.03. The standardized bias of all the covariates is largely reduced after matching. The *t*-test results confirm that the means of the two groups are similar after matching. These checks validate that the matching method is appropriate for producing similar groups.

We repeat the DID analysis using the matched samples. Panel A of Table 5 presents the results using one-to-one matching without replacement-matched samples. The number of matched sample users is 280. Panel B of Table 5 presents the results using one-to-four nearest neighbors matching with replacement-matched samples. The number of users in the matched sample is 461. After the matched samples are used, the results in Table 5 suggest that the average numbers of answers and articles per month increased by 10.9% and 31.9%, respectively, after users received the financial rewards. The results support H1a and H1b. By contrast, for knowledge seeking behaviors, users did not change their behaviors after receiving financial rewards. This result does not lend support for H2. For social activities, using the matched samples, Columns (7) and (9) in Table 5 respectively show the number of new followers increasing by 66.3%, and the number of new followees also increased by 26.7% after receiving the financial

Table 3. Ruling Out Spring Festivals Effects

	Answer$_{it}$		*Article*$_{it}$		*Ask*$_{it}$		*Follower*$_{it}$		*Follower*$_{it}$	
DV:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Live Feature Release as the Shock										
TreatGroup$_i$	–	0.091	–	0.345***	–	-0.018	–	2.624***	–	0.156**
		(0.064)		(0.047)		(0.013)		(0.084)		(0.068)
TreatGroup$_i$	0.109**	0.0812*	0.320***	0.316***	0.016	0.013	0.314***	0.263***	0.173***	0.160***
×*PostTreatment*$_{it}$	(0.043)	(0.043)	(0.031)	(0.031)	(0.012)	(0.012)	(0.056)	(0.054)	(0.046)	(0.046)
logFav$_{it-1}$	(0.012)	0.00969*	0.003	0.0105***	–0.0100**	0.001	0.030	0.377***	–0.028	0.006
	(0.017)	(0.005)	(0.004)	(0.002)	(0.005)	(0.001)	(0.023)	(0.012)	(0.021)	(0.008)
logUpvote $_{it-1}$	–0.0400**	0.116***	0.002	0.0184***	0.001	0.0112***	0.134***	0.262***	0.010	0.0714***
	(0.019)	(0.006)	(0.003)	(0.002)	(0.006)	(0.001)	(0.029)	(0.011)	(0.022)	(0.007)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,337	36,337	36,337	36,337	36,337	36,337	36,337	36,337	36,337	36,337
R-squared	0.005	0.125	0.04	0.205	0.001	0.014	0.042	0.617	0.009	0.037
# of users	5,191		5,191		5,191		5,191		5,191	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS
Panel B: First Live Event as the Shock										
TreatGroup$_i$	–	0.157**	–	0.398***	–	-0.012	–	2.581***	–	0.216***
		(0.063)		(0.047)		(0.013)		(0.082)		(0.068)
×*PostTreatment*$_{it}$	0.0665*	–0.061	0.424***	0.378***	0.019	0.007	0.516***	0.572***	0.182***	0.094
	(0.040)	(0.052)	(0.034)	(0.042)	(0.012)	(0.015)	(0.068)	(0.069)	(0.055)	(0.066)
logFav$_{it-1}$	–0.012	0.00972*	0.002	0.0102***	–0.0101**	0.001	0.029	0.376***	-0.028	0.006
	(0.017)	(0.005)	(0.004)	(0.002)	(0.005)	(0.001)	(0.023)	(0.012)	(0.021)	(0.008)
logUpvote $_{it-1}$	–0.0391**	0.116***	0.002	0.0184***	0.001	0.0112***	0.133***	0.262***	0.010	0.0715***
	(0.019)	(0.006)	(0.003)	(0.002)	(0.006)	(0.001)	(0.029)	(0.011)	(0.022)	(0.007)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,337	36,337	36,337	36,337	36,337	36,337	36,337	36,337	36,337	36,337
R-squared	0.004	0.125	0.056	0.209	0.001	0.014	0.046	0.618	0.009	0.036
# of users	5,191		5,191		5,191		5,191		5,191	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS

Notes: Clustered-robust standard errors (clustered on users) are reported in parentheses. ***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

Table 4. Summary Statistics of Control and Treat Group Before and After Matching

	Unmatched		Mean		%reduction	*t*-test	
Variable	Matched	Treated	Control	%bias	bias	*t*	*p* > *t*
gender	U	0.772	0.713	13.7	64.1	1.84	0.065
	M	0.750	0.771	−4.9		−0.42	0.676
loganswer	U	4.669	3.673	75.9	95.5	10.37	0
	M	4.375	4.420	−3.4		−0.29	0.768
logarticle	U	2.389	0.167	196.1	96.3	45.07	0
	M	2.004	2.087	−7.3		−0.46	0.648
logask	U	1.616	1.379	19.0	88.2	2.86	0.004
	M	1.502	1.530	−2.3		−0.19	0.850
logfollower	U	9.791	5.441	275.3	99.4	41.23	0
	M	9.104	9.131	−1.8		−0.16	0.875
logfollowee	U	4.854	4.535	24.9	60.8	3.29	0.001
	M	4.697	4.822	−9.8		−0.80	0.424
logupvote	U	9.921	6.391	209.6	98.9	27.11	0
	M	9.399	9.439	−2.4		−0.22	0.826
logfav	U	9.405	5.692	205.0	99.8	29.24	0
	M	8.850	8.859	−0.5		−0.04	0.967

Note: The comparisons are based on one-to-one matching without replacement (caliber = 0.03).

rewards from the paid knowledge exchange activity. These results support H3a and H3b. The estimation results using one-to-four nearest matching samples are similar to those using one-to-one matching samples (see Panel B in Table 5).

Falsification Tests

We perform two falsification tests to assess whether our main results are spurious. In our first falsification test, we assess the presence of the spillover effects of the financial incentive-based "Live" feature if users do not use the feature within the study period. Considering that our DID estimations rely on the assumption that the financial incentive-based feature only exerts an influence on those participants, we randomly assign 5% of all users (excluding the actual Live session holders) in our analysis to be Live session holders (the number of placebo Live session holders was 203, which was approximately equal to the number of actual Live holders.) We rerun our DID model. Table 6 presents the results of the first falsification test. The coefficients of the interaction term show no significant effects of the financial incentive-based feature on related engagement behaviors, thus increasing our confidence that the spillover effects on related engagement behaviors are caused by participating in the financial incentive-based feature.

Table 5. Results Based on DID and PSM

DV:	$Answer_{it}$		$Article_{it}$		Ask_{it}		$Follower_{it}$		$Followee_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: One-to-one matching without replacement matched samples										
$TreatGroup_i$	–	0.130	–	–0.043	–	–0.023	–	0.714***	–	0.241**
		(0.100)		(0.077)		(0.030)		(0.140)		(0.107)
$TreatGroup_i \times PostTreatment_{it}$	0.109*	0.060	0.319***	0.288***	0.002	–0.003	0.663***	0.596***	0.267***	0.238***
	(0.064)	(0.060)	(0.045)	(0.047)	(0.015)	(0.016)	(0.092)	(0.092)	(0.069)	(0.069)
$logFav_{it-1}$	–0.102	–0.111**	–0.017	–0.124***	–0.008	–0.0306*	0.082	0.142**	–0.239**	0.032
	(0.159)	(0.050)	(0.061)	(0.045)	(0.014)	(0.016)	(0.111)	(0.067)	(0.092)	(0.043)
$logUpvote_{it-1}$	–0.062	0.259***	–0.103*	0.189***	0.012	0.0662**	0.227*	0.624***	0.152*	0.113**
	(0.157)	(0.060)	(0.057)	(0.050)	(0.025)	(0.027)	(0.128)	(0.080)	(0.086)	(0.057)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,240	2,240	2,240	2,240	2,240	2,240	2,240	2,240	2,240	2,240
R-squared	0.02	0.073	0.058	0.065	0.005	0.038	0.157	0.535	0.028	0.077
# of users	280		280		280		280		280	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS
Panel B: One-to-four nearest neighbors matching with replacement matched samples										
$TreatGroup_i$	–	0.040	–	0.081	–	–0.026	–	1.133***	–	0.149*
		(0.080)		(0.058)		(0.023)		(0.108)		(0.086)
$TreatGroup_i \times PostTreatment_{it}$	0.0955*	0.060	0.321***	0.306***	0.011	0.008	0.421***	0.382***	0.245***	0.231***
	(0.053)	(0.050)	(0.038)	(0.038)	(0.014)	(0.014)	(0.071)	(0.071)	(0.057)	(0.057)
$logFav_{it-1}$	–0.052	–0.0868**	–0.007	–0.0552**	0.013	–0.010	0.053	0.205***	–0.149**	–0.008
	(0.061)	(0.040)	(0.033)	(0.026)	(0.009)	(0.008)	(0.063)	(0.043)	(0.063)	(0.029)
$logUpvote_{it-1}$	–0.049	0.219***	–0.020	0.110***	–0.002	0.0325***	0.350***	0.564***	0.0817*	0.115***
	(0.063)	(0.040)	(0.022)	(0.028)	(0.014)	(0.012)	(0.059)	(0.041)	(0.044)	(0.028)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,688	3,688	3,688	3,688	3,688	3,688	3,688	3,688	3,688	3,688
R-squared	0.017	0.086	0.064	0.092	0.003	0.022	0.12	0.644	0.02	0.063
# of users	461		461		461		461		461	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS

Notes: Clustered-robust standard errors (clustered on users) are reported in parentheses. ***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

Table 6. Estimation Results of the First Falsification Test

	$Answer_{it}$		$Article_{it}$		Ask_{it}		$Follower_{it}$		$Followee_{it}$	
DV:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$TreatGroup_i$	–	0.028	–	0.005	–	0.013	–	–0.030	–	0.117**
		(0.041)		(0.017)		(0.013)		(0.067)		(0.054)
$TreatGroup_i\times$	0.003	0.010	0.004	0.004	0.000	0.000	–0.008	–0.006	–0.002	0.000
$PostTreatment_{it}$	(0.024)	(0.025)	(0.006)	(0.006)	(0.007)	(0.007)	(0.034)	(0.035)	(0.036)	(0.036)
$logFav_{it-1}$	–0.001	0.0110**	0.00827***	0.00983***	–0.003	0.001	0.0344**	0.378***	–0.029	0.006
	(0.013)	(0.005)	(0.003)	(0.002)	(0.003)	(0.001)	(0.017)	(0.012)	(0.017)	(0.008)
$logUpvote_{it-1}$	–0.0534***	0.116***	0.00735***	0.0158***	0.000	0.0112***	0.138***	0.258***	0.018	0.0731***
	(0.018)	(0.006)	(0.003)	(0.002)	(0.005)	(0.001)	(0.026)	(0.011)	(0.022)	(0.007)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,904	39,904	39,904	39,904	39,904	39,904	39,904	39,904	39,904	39,904
R-squared	0.009	0.106	0.003	0.037	0.001	0.014	0.033	0.459	0.008	0.026
# of users	4,988		4,988		4,988		4,988		4,988	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS

Notes: Clustered-robust standard errors (clustered on users) are reported in parentheses. $***p < 0.01$. $**p < 0.05$. $*p < 0.1$.

In our second falsification test, we check whether the behavior trends for Live session holders and non-Live session holders differ significantly before Live was launched. To check conduct this test, we select March 17, 2016, April 17, 2016, and May 16, 2016, dates prior to the actual Live's launch time as the cut-off dates. With these placebo cut-off dates, if the Live session holders perform significantly higher engagement behavior than the non-Live session holders, then it means that the main results are spurious because the financial incentive-based program should not have affected the users' engagement behaviors before Live was launched. We employ the DID estimation model by regressing the dependent variables on the interaction terms of $Treatment_i$ with dummy variables for the three placebo cut-off dates. In this analysis, we limit the study period from January 17, 2016 to May 16, 2016. Table 7 presents the results using April 17, 2016 as the cut-off date time. The trends of engagement behaviors (except for voluntary answering behavior) for Live session holders and non-Live session holders are consistent prior to Live's launch. By contrast, the Live session holders decrease their voluntary answering activities over time prior to May 16, 2016. We argue that the users' voluntary answering behavior appears to be declining over time, especially the relatively active users (Live session holders who have more engagement behaviors than non-Live session holders). The emergence of a financial incentive-based feature changed this declining trend (see results in Table 7). The results with March 17, 2016 as the cutoff time are omitted for brevity, and they are identical to the results in Table 7.

Relative Time Model

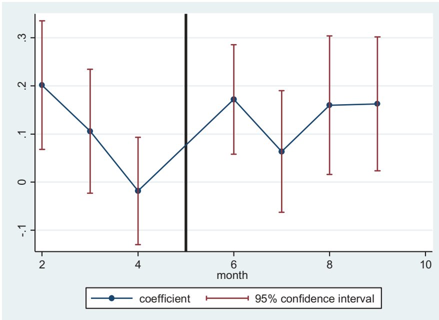
To test the key assumption of the DID specification, the parallel trend assumption, we explore how our dependent variables change between the treated and control groups before launching Live by adding a set of interaction terms of monthly dummies and treatment indicator variable in our estimation equation (Equation 2). Specifically, we apply this relative time analysis in references to several papers in the recent IS literature [23, 49]. The logic of this test is that, if there is an existing trend in the dependent variable prior to the Live feature release that is in the same direction as the trends after launching Live, our main results may be driven by some other events that happened prior to the Live feature release. On the contrary, if the there is no clear trend prior to the launch of the Live feature, yet the effect manifests after the launch of the Live feature, we can gain increased confidence in our main results and attribute the observed effects to the policy change.

In our econometric specification, we use the month of launching Live as the reference group. Thus, we omit the interaction term of the month of launching Live (May 2016) and the treatment indicator variable. If $TreatGroup_i$ equals 1, the result indicates that individual i belongs to the treated group; otherwise, the individual i belongs to the control group. $MonthDummy_j$ indicates the monthly dummy variable. Figure 4 illustrates the coefficients of the interaction terms.

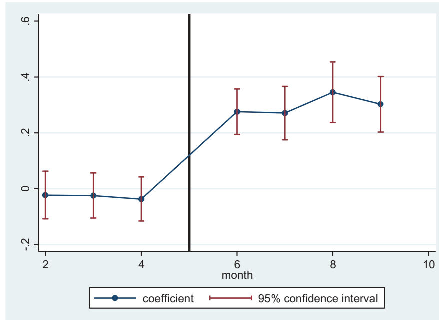
Table 7. Estimation Results of the Second Falsification Test

	$Answer_{it}$		$Article_{it}$		Ask_{it}		$Follower_{it}$		$Followee_{it}$	
DV:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$TreatGroup_i$	–	0.233***	–	0.361***	–	–0.008	–	2.706***	–	0.155**
		(0.074)		(0.046)		(0.015)		(0.090)		(0.070)
$TreatGroup_i\times$	–0.150***	–0.181***	0.005	0.004	–0.012	–0.013	0.006	–0.025	0.016	0.000
$PostTreatment_{it}$	(0.051)	(0.052)	(0.029)	(0.029)	(0.016)	(0.016)	(0.043)	(0.045)	(0.048)	(0.050)
$logFav_{it-1}$	0.005	0.004	0.0054*	0.00720***	0.003	0.001	0.0351**	0.364***	0.003	0.010
	(0.011)	(0.006)	(0.003)	(0.002)	(0.003)	(0.001)	(0.014)	(0.012)	(0.017)	(0.010)
$logUpvote_{it-1}$	–0.174***	0.122***	0.006	0.0170***	–0.001	0.0119***	–0.028	0.262***	–0.040	0.0683***
	(0.033)	(0.007)	(0.005)	(0.003)	(0.008)	(0.002)	(0.031)	(0.012)	(0.043)	(0.010)
Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,764	20,764	20,764	20,764	20,764	20,764	20,764	20,764	20,764	20,764
R-squared	0.025	0.117	0.003	0.131	0.001	0.014	0.012	0.6	0.007	0.032
# of users	5,191		5,191		5,191		5,191		5,191	
Specification	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS

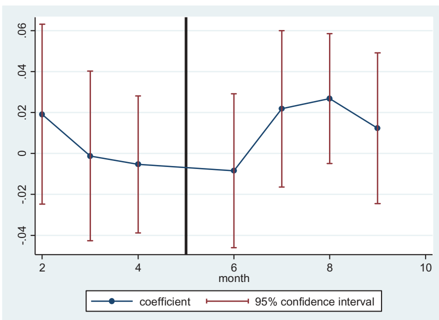
Notes: Clustered-robust standard errors (clustered on users) are reported in parentheses. ***$p < 0.01$. **$p < 0.05$. * $p < 0.1$.



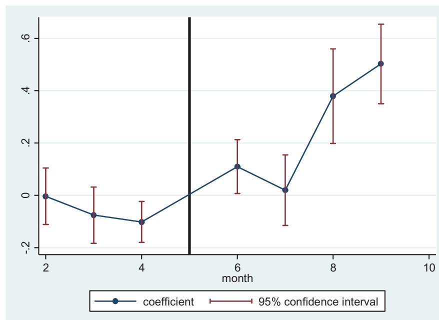
a.Answer



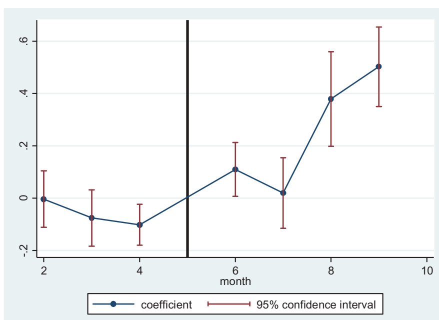
b.Article



c.Ask



d. Follower



e. Followee

Figure 4. Relative Time Model Estimates.

$$y_{it} = \beta_0 + \beta_1 * TreatmentGroup_i * MonthDummy_t + \beta_2 * logFav_{t-1} + \beta_3 * logUpvote_{t-1} + \sum MonthDummy_t + \alpha_i + \epsilon_{it} \quad (2)$$

Besides the relative time model, we conducted a number of extensions to the main analyses, which offers insights beyond the main findings. Please refer to the online supplemental information for the extensions.

Discussion

Key Findings

Given the intense competition of knowledge exchange platforms, certain knowledge exchange platforms take a series of measures to increase their competitiveness, such as implementing financial incentive-based services to stimulate user engagement. Our study investigated the unintended spillover effects of the financial incentive-based feature on users' related engagement behaviors, which can inspire users' involvement and significantly enhance their loyalty to the knowledge exchange platforms. Specifically, we examine the spillover effects of the financial incentive on users' voluntary knowledge sharing behaviors, knowledge seeking behaviors, and social behaviors in a knowledge exchange platform. Methodologically, our study leverages the natural experimental data and employs the panel data DID framework for estimations. To address the self-selection problem, we employ propensity score matching to match the treated and control groups, further enhancing the causal identifications. Based on the matched samples, users are found to increase voluntary knowledge sharing and establish further social ties with other users in knowledge exchange platforms after receiving financial rewards from the financial incentive-based feature. However, there is no evidence to suggest users will decrease in their knowledge seeking behaviors.

Building on motivation theory and equity theory, we argue that when users receive financial incentives from the websites, they will likely commit extra time and effort to the platforms because the financial rewards can be regarded as an acknowledgment of their self-efficacy, which will crowd in users' intrinsic motivation. Thus, the enhancement of intrinsic motivation and the attempt not to be perceived as a person who intends his own gains will motivate users to reciprocate others in the site by voluntarily sharing more knowledge [13, 18]. At the same time, we originally proposed that the knowledge seeking behaviors will decrease after users receive financial rewards because they want to maintain their knowledgeable image. However, users appeared to maintain the need to seek knowledge in knowledge exchange platforms and did not significantly change their knowledge seeking behaviors after receiving financial rewards. The financial rewards received from the website will likewise evoke users' loyalty to the platform and closeness to other users on the websites. The users will display willingness to build social ties with other users in knowledge exchange platforms.

Our study also explores how the relationship between the financial incentive and related users' engagement behaviors differs with the amount of financial incentives. High financial incentives can exert strong influences on related engagement behaviors. In our further analysis, users increased their voluntary knowledge sharing behaviors in the first month after pushing out Live, although they did not hold Live sessions in this period. A potential explanation is that users want to increase their publicity and enhance their prestige to prepare for holding Live sessions in the future by altering their existing behaviors. Moreover, we use May 16, 2016 as the cut-off date to analyze the effects of the financial incentive-based feature. Users' engagement in voluntary knowledge sharing behaviors and social-tie-building behaviors were more intensive after they received the financial rewards compared to before they received the financial rewards.

Implications

Our paper contributes to the prior literature on multiple fronts. First, we contribute to the literature on the effectiveness of financial rewards in changing users' behaviors from a new perspective. The current study is different from previous research, which examined the effectiveness of financial incentives from the viewpoint of behaviors targeted by financial rewards [5, 28, 42]. Based on motivation theory and equity theory, the current study explores the spillover effects of the financial incentives in on users' non-incentivized engagement behaviors in the context of online knowledge exchange platforms. In addition, we further explore the different spillover effects of different amounts of financial rewards. Indeed, financial incentives influence users' related engagement behaviors, and the influence is determined by the amount of financial rewards.

Second, we complement the literature on users' engagement behaviors in knowledge exchange platforms, wherein users play multiple roles. Users generally utilize knowledge exchange platforms to seek knowledge and learn skills of interest [33, 47]. Users are also willing to share their experience and answer others' questions on these platforms. As they engage with the platform through knowledge seeking and contributing, users also establish social ties with other like-minded users [33]. Thus, knowledge sharing behaviors, knowledge seeking behaviors, and social behaviors are equally indispensable for the development of knowledge exchange platforms. Previous studies primarily focused on the antecedents or intervention strategies that motivate knowledge or content contribution [23, 21, 34], while neglecting the knowledge seeking behaviors and social engagement behaviors in knowledge exchange platforms. Our study filled in this gap by comprehensively examining a multitude of engagement behaviors.

Our study also has important managerial implications for online communities that depend on UGC and users' social interactive behaviors. To fully understand the effects of financial incentives, it is imperative to go beyond the incentivized behaviors, to deepen our understanding of the potential spillover effects of financial incentives. Launching a financial incentive-based feature in the knowledge exchange platform can affect both voluntary knowledge sharing and social activities. However, participating in the paid knowledge sharing activity will not reduce users' knowledge seeking behaviors. Such effects should also be generalized to other online communities that rely on user-generated content and knowledge to thrive, such as OSS sites and online product review platforms. As financial incentives can motivate users to participate in not just the incentivized activities, but also other beneficial online activities, managers of the online communities or platforms should embrace financial incentives when they consider effective approaches to seed, stimulate, and nurture user engagement. For example, the cold-start and under provision of content is of particular concern for many new communities [5, 21]. The spillover effects of financial incentives can create cascading effects for user engagement, as more content will attract more readers, who in turn motivate more engagement from the content creators. Therefore, our study suggests that financial incentives can be an effective content seeding strategy.

Limitations and Future Research

This study contains several limitations, which also open up multiple potentially fruitful opportunities for future research. First, it only investigates the effect of financial incentive on the quantity of engagement behaviors. Nevertheless, the quality of engagement activity is equally important for online platforms [7, 34]. Although our results suggest that users will increase their voluntary knowledge sharing behaviors in knowledge exchange platforms after receiving financial rewards from paid knowledge sharing activities, it is unclear whether the length and quality of answers and articles also increase with the quantity. In addition, although Live session holders build more social ties in the knowledge exchange platforms than before, no evidence proves that Live session holders will have further interactions with new friends in knowledge exchange platforms. The effect of financial incentives on the quality of engagement behaviors will require research in the future. Second, we only study the spillover effects of financial incentives for a period of four months because of data availability. Whether the spillover effects will sustain in a longer time period warrants further study. Notably, this question is essential for website managers because the financial incentive-based feature motivates users to participate in other online activities for a certain period of time, which may become ineffective once users no longer receive financial rewards or receive adequate financial rewards from the website. Third, although we have used propensity score matching in tandem with the difference-in-differences estimation, we acknowledge that users' selection into the feature adoption may still pose an endogeneity concern that is not fully resolved. To fully resolve such an endogeneity issue, a randomized field experiment may be required, and future research may explore this direction to further uncover the spillover effects of financial incentives.

Conclusion

Leveraging a unique data set from an online knowledge exchange platform, we conducted a difference-in-differences analyses combined with propensity score matching to analyze the spillover effects of introducing financial incentives to the platform on users' engagement behaviors. The empirical results from our study suggest that the financial incentives not only have a positive effect on incentivized engagement, but also have spillover effects to users' other desirable non-incentivized online engagement behaviors, such as further knowledge sharing and social engagement on the platform. Our study extends prior literature by improving our understanding on the overall positive effect of financial incentives above and beyond their first-order outcomes. Given the divergent industry practice in using financial incentives for user engagement, our research provides empirical evidence in support of using financial incentives in practice, as they can be used as an effective strategy to nurture users, to seed content, and to enhance sociality of a digital platform.

Acknowledgment: Authors would like to thank the anonymous reviewers for their constructive feedback. All authors made equal contributions to the paper. Zhijun Yan is the corresponding author of this paper.

Funding

Zhijun Yan acknowledges financial support from National Natural Science Foundation of China (Grant #: 71572013, 71872013, 71521002, 71432002).

Notes

1. Consistent with the extant literature [17], we use "asker" to refer to users who ask questions and "answerer" to refer to users who answer questions.
2. In the fan club meeting on May 14th, 2016, Zhihu announced that it will launch of the "Zhihu Live" feature (http://tech.sina.com.cn/i/2016-05-14/doc-ifxsenvm0417657.shtml). And the launching time of the first "Zhihu Live" on the website was May 16th, 2016.

Supplemental Material

Supplemental data for this article can be accessed on the publisher's website.

References

1. Acland, D.; and Levy, M.R. Naiveté. Projection bias, and habit formation in gym attendance. *Management Science*, *61*, 1 (2015), 146–160.
2. Adams, J.S. Towards an understanding of inequity. *The Journal of Abnormal and Social Psychology*, *67*, 5 (1963), 422–436.
3. Beck, R.; Pahlke, I.; and Seebach, C. Knowledge exchange and symbolic action in social media-enabled electronic networks of practice: A multilevel perspective on knowledge seekers and contributors. *MIS Quarterly*, *38*, 4 (2014), 1245–1270.
4. Bolton, R.N.; Kannan, P.K.; and Bramlett, M.D. Implications of loyalty program membership and service experiences for customer retention and value. *Journal of the Academy of Marketing Science*, *28*, 1 (2000), 95–108.
5. Burtch, G.; Hong, Y.; Bapna, R.; and Griskevicius, V. Stimulating online reviews by combining financial incentives and social norms. *Management Science*, *64*, 5 (2017), 2065–2082.
6. Chai, S.; Das, S.; and Rao, H.R. Factors affecting bloggers' knowledge sharing: An investigation across gender. *Journal of Management Information Systems*, *28*, 3 (2011), 309–342.

7. Chen, Y.; Ho, T.H.; and Kim, Y.M. Knowledge market design: A field experiment at Google answers. *Journal of Public Economic Theory*, *12*, 4 (2010), 641–664.

8. Chiu, C.M.; Hsu, M.H.; and Wang, E.T.G. Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. *Decision Support Systems*, *42*, 3 (2006), 1872-1888.

9. Davenport, T.H.; and Grover, V. Special issue: Knowledge management. *Journal of Management Information Systems*, *18*, 1 (2001), 3–4.

10. Deci, E.L.; and Ryan, R.M. *Intrinsic motivation and self-determination in human behavior*. Springer Science and Business Media, (1985) 43–85.

11. Dellarocas, C.; Gao, G.; and Narayan, R. Are consumers more likely to contribute online reviews for hit or niche products? *Journal of Management Information Systems*, *27*, 2 (2010), 127–158.

12. Durcikova, A.; and Gray, P. How knowledge validation processes affect knowledge contribution. *Journal of Management Information Systems*, *25*, 4 (2009), 81–108.

13. Feng, Y.; and Ye, H. Why do you return the favor in online knowledge communities? A study of the motivations of reciprocity. *Computers in Human Behavior*, *63*(2016), 342–349.

14. Garnefeld, I.; Iseke, A.; and Krebs, A. Explicit incentives in online communities: Boon or bane? *International Journal of Electronic Commerce*, *17*, 1 (2012), 11–38.

15. Gneezy, U.; and Rustichini, A. Pay enough or don't pay at all. *The Quarterly Journal of Economics*, *115*, 3 (2000), 791–810.

16. Gneezy, U.; Meier, S.; and Rey-Biel, P. When and why incentives (don't) work to modify behavior. *Journal of Economic Perspectives*, *25*, 4 (2011), 191–209.

17. Goes, P.B.; Guo, C.; and Lin, M. Do incentive hierarchies induce user effort? Evidence from an online knowledge exchange. *Information Systems Research*, *27*, 3 (2016), 497–516.

18. Green, J.D. Looking at me, appreciating you: Self-focused attention distinguishes between gratitude and indebtedness. *Cognition and Emotion*, *24*, 4 (2010), 710–718.

19. Guo, S.; Guo, X.; Fang, Y.; and Vogel, D. How doctors gain social and economic returns in online health-care communities: a professional capital perspective. *Journal of Management Information Systems*, *34*, 2 (2017), 487–519.

20. Hsieh, G.; Kraut, R.E.; and Hudson, S.E. Why pay?: Exploring how financial incentives are used for question & answer. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, (2010), 305–314.

21. Huang, N.; Burtch, G.; Gu, B.; Hong, Y.; Liang, C.; Wang, K.; Fu, D.; and Yang, B. Motivating user-generated content with performance feedback: Evidence from randomized field experiments. *Management Science*, (2018), forthcoming.

22. Hung, S.Y.; Durcikova, A.; Lai, H.M.; and Lin, W.M. The influence of intrinsic and extrinsic motivation on individuals' knowledge sharing behavior. *International Journal of Human - Computer Studies*, *69*, 6 (2011), 415–427.

23. Huang, N.; Hong, Y.; and Burtch, G. Social network integration and user content generation: Evidence from natural experiments. *MIS Quarterly*, *41*, 4 (2017), 1035–1058.

24. Huseman, R.C.; Hatfield, J.D.; and Miles, E.W. A new perspective on equity theory: The equity sensitivity construct. *Academy of Management Review*, *12*, 2 (1987), 222–234.

25. Jeon, G.Y.; Kim, Y.-M.; and Chen, Y. Re-examining price as a predictor of answer quality in an online Q&A site. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, (2010), 325–328.

26. Khansa, L.; Ma, X.; Liginlal, D.; and Kim, S.S. Understanding members' active participation in online question-and-answer communities: A theory and empirical analysis. *Journal of Management Information Systems*, *32*, 2 (2015), 162–203.

27. Lee, U.; Kim, J.; Yi, E.; Sung, J.; and Gerla, M. Analyzing crowd workers in mobile pay-for-answer q&a. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, (2013), 533–542.

28. Lu, Y.; Ou, C.; and Angelopoulos, S. Exploring the effect of monetary incentives on user behavior in online sharing platforms. *Proceedings of the 51st Hawaii International Conference on System Sciences*, (January 2018).

29. Mochon, D.; Schwartz, J.; Maroba, J.; Patel, D.; and Ariely, D. Gain without pain: The extended effects of a behavioral health intervention. *Management Science*, *63*, 1 (2016), 58–72.

30. Monic, S.; and Feng, Z. Ad revenue and content commercialization: Evidence from blogs. *Management Science*, *59*, 10 (2013), 2314–2331.

31. Osterloh, M.; and Frey, B.S. Motivation, knowledge transfer, and organizational forms. *Organization Science*, *11*, 5 (2000), 538–550.

32. Ozer, M.; and Vogel, D. Contextualized relationship between knowledge sharing and performance in software development. *Journal of Management Information Systems*, *32*, 2 (2015), 134–161.

33. Phang, C.W.; Kankanhalli, A.; and Sabherwal, R., 2009. Usability and sociability in online communities: A comparative study of knowledge seeking and contribution. *Journal of the Association for Information Systems*, *10*, 10 (2009), 721–747.

34. Qiu, L.; and Kumar, S. Understanding voluntary knowledge provision and content contribution through a social-media-based prediction market: A field experiment. *Information Systems Research*, *28*, 3 (2017), 529–546.

35. Raban, D.R. The incentive structure in an online information market. *Journal of the Association for Information Science and Technology*, *59*, 14 (2008), 2284–2295.

36. Raban, D.R. Self-presentation and the value of information in Q&A websites. *Journal of the Association for Information Science and Technology*, *60*, 12 (2009), 2465–2473.

37. Ren, Y.; Harper, F.M.; Drenner, S.; Terveen, L.; Kiesler, S.; Riedl, J.; and Kraut, R.E. Building member attachment in online communities: Applying theories of group identity and interpersonal bonds. *MIS Quarterly*, *36*, 3 (2012), 841–864.

38. Roberts, J.A.; Hann, I.-H.; and Slaughter, S.A. Understanding the motivations, participation, and performance of open source software developers: A longitudinal study of the apache projects. *Management Science*, *52*, 7 (2006), 984–999.

39. Royer, H.; Stehr, M.; and Sydnor, J. Incentives, commitments, and habit formation in exercise: Evidence from a field experiment with workers at a fortune-500 company. *American Economic Journal: Applied Economics*, *7*, 3 (2015), 51–84.

40. Ruth, R.D. Conversation as a source of satisfaction and continuance in a question-and-answer site. *European Journal of Information Systems*, *21*, 4 (2012), 427–437.

41. Ryan, R.M.; and Deci, E.L. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, *25*, 1 (2000), 54–67.

42. Shriver, S.K.; Nair, H.; and Hofstetter, R. Social ties and user-generated content: Evidence from an online social network. *Management Science*, *59*, 6 (2013), 1425–1443.

43. Sun, Y.; Dong, X.; and McIntyre, S. Motivation of user-generated content: Social connectedness moderates the effects of financial rewards. *Marketing Science*, *36*, 3 (2017), 329–337.

44. Tang, Q.; Gu, B; and Whinston, A.B. Content contribution for revenue sharing and reputation in social media: A dynamic structural model. *Journal of Management Information Systems*, *29*, 2 (2012), 41–76.

45. Volpp, K.G.; Troxel, A.B.; Pauly, M.V.; Glick, H.A.; Puig, A.; Asch, D.A.; Galvin, R.; Zhu, J.; Wan, F.; and DeGuzman, J. A randomized, controlled trial of financial incentives for smoking cessation. *New England Journal of Medicine*, *360*, 7 (2009), 699–709.

46. Von Krogh, G.; Haefliger, S.; Spaeth, S.; and Wallin, M.W. Carrots and rainbows: Motivation and social practice in open source software development. *MIS Quarterly*, *36*, 2 (2012), 649–676.

47. Wasko, M.M.; and Faraj, S. Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, *29*, 1 (2005), 35–57.

48. Wills, T.A. Perceptions of clients by professional helpers. *Psychological Bulletin*, *85*, 5 (1978), 968.

49. Xu, K.Q.; Chan, J.; Ghose, A.; and Han, S.P. Battle of the channels: The impact of tablets on digital commerce. *Management Science*, *63*, 5 (2017), 1469–1492.

50. Yang, J.; Wei, X.; Ackerman, M.S.; and Adamic, L.A. Activity lifespan: An analysis of user survival patterns in online knowledge sharing communities. *Proceedings of the International Conference on Weblogs and Social Media*, ICWSM, (May 2010), 186–193.

51. Zhang, X.; and Wang, C. Network positions and contributions to online public goods: The case of Chinese Wikipedia. *Journal of Management Information Systems*, *29*, 2 (2012), 11–40.

52. Zhao, L.; Detlor, B.; and Connelly, C.E. Sharing knowledge in social Q&A sites: The unintended consequences of extrinsic motivation. *Journal of Management Information Systems*, *33*, 1 (2016), 70–100.

53. Zwass, V. Co-creation: Toward a taxonomy and an integrated research perspective. *International Journal of Electronic Commerce*, *15*, 1 (2010), 11–48.