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Chat More and Contribute Better: An Empirical Study of a Knowledge-Sharing Community

Chat More and Contribute Better: An Empirical Study of a Knowledge-Sharing Community*

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Abstract

We analyze whether an informal second channel for communication can improve the efficiency of knowledge transfer in an electronic network of practice. We explore this question by analyzing the effect of chat rooms in the well-known Q&A forum Stack Overflow. We identify the causal effect using a difference-in-differences approach, which exploits a feed functionality that non-selectively pushed all questions from the Q&A into the relevant chat rooms. We report two main findings: First, chat rooms reduced the time until a question in the main Q&A received a satisfactory answer. Second, chat rooms disproportionately benefited new users who asked low-quality questions. Our study has clear managerial implications: A second channel for communication can complement the main channel in online communities to enhance both efficiency and inclusion.

Keywords: Knowledge sharing, Online community, User contribution

JEL Classification Codes: L17, O31, O36

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1. Introduction

In the digital age, the sharing of practice-related knowledge, such as programming and legal advice, often comes through computer- and internet-based communication technologies known as electronic networks of practice (Wasko and Faraj 2005). These networks of practice have been found to be an effective means of transferring knowledge across users (Boudreau and Lakhani 2009) and, as a result, have grown rapidly in recent years. For example, the discussion forum Stack Overflow has over 100 million users (Fullerton 2019), and a recent survey of that site shows that over 85% of its users visit the site multiple times per week (Stack Overflow 2019); Quora reached 300 million monthly visitors in 2018 (Browne 2018); and Zhihu, the largest Chinese Q&A community, exceeded 220 million monthly visitors in 2018 (Wikipedia 2018).

Given the importance of these sites, recent research has sought to identify and improve design features that will improve interactions within them. Much of this line of work has sought to identify design choices that will improve user contributions (e.g., Wasko and Faraj 2005; Jabr et al. 2014; Goes, Guo, and Lin 2016). However, although stimulating user contributions is important for the success of knowledge-sharing platforms, insufficient contributions are not the only barrier to effective knowledge transfer. In particular, many networks of practice incorporate specific conventions, such as gamification, that encourage contributions. However, these conventions may, at the same time, create barriers to community participation by certain groups, such as new users (Ford, Lustig, Banks, and Parnin 2018; Ford, Smith, Guo, and Parnin 2016; Valisescu, Capiluppo, and Serebrenik 2014) when members enforce community norms (Yang 2020).

Online communities have recently explored adding new virtual spaces that, though they lack well-known features such as gamification that encourage contributions, may facilitate informal conversations among users. These spaces, sometimes called “third places” because of their similarity to offline community meeting places such as cafes and coffee shops (Oldenburg 1999), have become increasingly popular—for example, Wikipedia Talk pages, which provide a place for editors to interact informally and discuss edits to Wikipedia pages, and the group chat feature in Reddit. These pages provide a place for users to interact with fewer formal norms and, in doing so, may improve outcomes in the core community. However, to our knowledge little formal assessment has been performed on the impact of these new spaces on networks of practice. This is a significant gap in understanding. If these spaces improve outcomes, then networks of practice should consider them a potential additional channel in which users can interact, particularly if they help new users, who may be unaware of norms in the core community.

In this paper, we examine how the introduction of a chat functionality affected the efficiency of knowledge exchange on Stack Overflow (SO), the largest online question and answer (Q&A) community for programmers. We measure the changes in the efficiency of the knowledge exchange on SO as the probability with which questions receive an accepted answer within one, two, four, or eight hours. Ideally, we would like to compare the efficiency of questions that are discussed in chat rooms to the efficiency of questions that do not appear in a chat room. However, because questions that appear in chat rooms might be fundamentally different from questions that do not appear in a chat room, a direct comparison of questions based on whether they appear in chat rooms may be contaminated by selection bias.

To overcome concerns about selection bias and identify the effect of interest, we exploit the feed function in the SO chat rooms. When a user turns on the feed function of the chat room, the feed pushes all newly generated questions that are related into the chat room. We build a difference-in-difference (DID) approach around the activation of a feed to identify the effect of chat rooms on the speed with which questions receive an acceptable answer.

Our findings suggest that chat rooms increase the efficiency of knowledge exchange in the main Q&A community: for example, when a question is pushed into the chat room of a Q&A community, the probability that the question will receive an accepted answer within two hours increases by 3.2 percentage points. A causal interpretation of this estimate is supported by a range of robustness analyses, including a pretrend analysis and an exploration of alternative control groups.

The implications of being pushed into chat rooms are not the same for all questions and question askers, however. They are strongest for questions that are less likely to receive an answer in the Q&A site, namely, those that are asked by new users and those that are of low quality. For example, one set of estimates shows that users with a reputation of zero or lower (i.e., negative) are 14.6 percentage points less likely than users with a positive reputation to receive an answer within two hours on the Q&A site. However, when questions from these users (with a zero or negative reputation) are pushed into the chat room, the likelihood of receiving an answer within two hours increases further, by 5.9 percentage points. We then decompose these effects based on user reputation and question quality, finding that the effects of the feed are strongest on questions that are of low quality and asked by new (low-reputation) users.

Our findings have several managerial implications, because they highlight the ability of less formal and complementary communication channels to support the transfer of knowledge in communities of practice. First, these additional channels can increase overall efficiency. Second, they can complement an efficiency-focused main channel by providing a space in which disadvantaged groups, such as newcomers, can benefit from a "more-welcoming" environment, which facilitates improved access to community knowledge.

2. Related Literature

Our research advances prior work that investigated the implications of platform governance choices on networks of practice, where sharing of practice-related knowledge is mediated through online channels, labeled electronic networks of practice (Wasko and Faraj 2005). One line of literature has investigated platform actions that increase the knowledge *contribution* of users (Raban 2008, Wasko and Faraj 2005, Wiertz and de Ruyter 2007 and Jabr, Mookerjee, Tan, and Mookerjee 2014) and their *commitment* to the community (Moon and Sproull 2008). One area of particular focus has been the implications of gamification, the process of adding gamelike features to something so as to encourage participation. Previous studies have shown that the addition of gamification incentives motivate user contributions (Jabr, Mookerjee, Tan, and Mookerjee 2014; Liu, Santhanam, and Webster 2017). Gamified elements, such as badges (Anderson et al 2013), status (Liu, Santhanam, and Webster 2017; Goes, Guo and Lin 2019), and feedback (Jabr, Mookerjee, Tan, and Mookerjee 2014; Moon and Sproull 2008), effectively motivate users to engage in online systems.

Although increases in user contributions increase the likelihood of knowledge transfer between network participants, they do not ensure it. It has long been known in other settings of computer-mediated communications that knowledge can be communicated without being absorbed by the intended recipient of the communication (Alavi and Leidner 2001). A few studies have discussed knowledge transfer and exchange activities among users (Wicks et al. 2012; Curran et al. 2009; Dinh et al. 2011), but they could not observe the extent to which the transmission of knowledge is efficient or successful. Increases in contributions might not lead to an improvement in outcomes, however. Our research contributes to two lines of work that explored different aspects of this problem.

First, incentives to drive contributions can indirectly affect outcomes for some community members. Within the context of research on electronic networks of practice such as SO, the existence of barriers to participation by groups such as newcomers and females is an active area of attention (Ford et al. 2016, 2018; Nian et al. 2019). We contribute to a line of literature that explores issues related to how newcomers can be integrated into online communities. Early research in this area is summarized in Kraut et al. (2012). For example, because newcomers are especially likely to leave the community if their first contribution is rejected (Halfaker, Kittur, and Riedl 2011; Zhang and Zhu 2006), online communities such as Wikipedia employ “don’t bite the newcomer” policies to reduce the negative impact of entry barriers on newcomers. More recent research has investigated how peer awards can disproportionately increase the engagement of users in communities (Burtch et al. 2020). The present paper contributes to this line of research by showing the implications of the introduction of a supportive channel on outcomes for new users relative to the rest of the community.

Second, it is possible that answers provided are not understood or absorbed by the person who originally posed the question. A long line of literature in information systems has explored the properties of different communication channels and their efficacy in different offline contexts (e.g., Daft and Lengel 1986; Daft et al. 1987; Dennis et al. 2008; George, Carlson, and Valacich 2013). One takeaway from this literature is that communication channels may show differential efficacy in different contexts. In online spaces, prior work has investigated the impact of introducing new communication channels in specific settings, such as open source development and education. For example, Shihab et al. (2009) and Elliott and Scacchi (2003) documented that the introduction of a supportive channel based on chat increased contributor retention and resolved conflicts in an open source project. Prior work has also investigated the implications of new online communication channels, such as chat, on learning outcomes (e.g., Coetzee, Fox, and Hartmann 2014). We further this line of work by identifying the benefits of a supportive channel in a popular electronic network of practice.

3. Research Context

SO is a large programming Q&A community in which users can pose and answer questions. In this section, we provide a brief overview of how the primary SO site functions and then offer an introduction to chat rooms. Last, we introduce the feed function, which plays a critical role in our identification strategy.

3.1 Stack Overflow Q&A Community

Users can ask and answer questions related to programming in the SO Q&A community. The user who poses the question ("askers") can post it, and other users can answer the question ("answerers"). We summarize key features that are important to our analysis.

Questions, answers, and accepted answers. A question can have multiple answers. All users can vote up or down on a question or an answer, and those votes are then summarized as the question or answer's "score" (up votes minus down votes). The users who pose the questions can select only one answer as the "accepted answer"—that is, the answer that they think successfully solves the question that was originally asked. The first answer is not always the accepted answer.

Tags. The asker of each question can assign tags to it indicating the programming language, framework, or related module. For example, in our data the set of tags for one question includes "c#" and "asp.net-mvc", which shows that this question needs to be answered by someone who uses c# language and is familiar with the asp.net-mvc framework. Users can assign multiple tags to a question to help potential answerers quickly identify whether they possess the expertise needed to answer the question.

User reputation system. SO uses a reputation system and badges to motivate users to contribute. Users can gain reputation points from the upvotes and downvotes of their questions or answers. These votes are assigned by the community members. For example, users gain 10 points for receiving an upvote, lose 2 points for receiving a downvote, and earn an extra 15 points if their answers are "accepted."

3.2 Stack Overflow Chat Rooms

In October 15, 2010, SO launched a chat room feature to allow users to interact in a manner that differs from that of the main Q&A community (Atwood 2010).[1] Chat rooms come in two major types: chat rooms for interest groups and discussion chat rooms. Discussion chat rooms are created on an ad hoc basis by users to discuss relatively narrow issues, such as a particular question on the Q&A forum. In contrast, chat rooms for an interest group serve as a forum for a large number of users who share a particular interest, usually based upon a programming language. For example, typical chat rooms for interest groups include those on c#, JavaScript, PHP, Python, and Lounge<C++>. In this paper, we focus on interest group chat rooms, rather than discussion chat rooms.

Questions on the main Q&A site can be added to the chat room through different means. First, they can be pushed into the chat rooms by the askers or by other users. Second, questions can be pushed into the chat rooms via feeds, i.e., bots that automatically push questions from the Q&A site to the chat rooms.

Chat room feeds can be turned on and off by users. After a feed is turned on for a chat room, it pushes all questions with a certain tag into the associated chat room. Figures 1a and 1b illustrate how the feed works. Figure 1a shows a question that was posed on December 21, 2013, with the tag "Perl." Figure 1b shows the question after it was pushed into the Perl chat room immediately after being asked, along with all other newly generated questions tagged "Perl." The question did not receive any response for four hours, and then the asker discusses the question with a potential answerer in the chat room and provides some clarification of the original question (see Figure 1b).

[Insert Figure 1a, Figure 1b here]

4. Theoretical Motivation: Benefits of Chat Rooms

In this section, we discuss the theoretical motivation for our hypotheses. We start by discussing differences in the operational characteristics of online forums and chat rooms in online communities, as well as their

[1] https://stackoverflow.blog/2010/04/29/do-trilogy-sites-need-a-third-place/.

implications for user behavior. We then examine the implications of these differences specifically in the context of an electronic network of practice such as Stack Overflow.

4.1. Differences in the Characteristics of Online Forums and Chat Rooms

Earlier Q&A communities used relatively unstructured forms of online communication, such as e-mail (e.g., Ahuja, Galletta, and Carley 2003) and online bulletin boards (Wasko and Faraj 2005). More recently, electronic networks of practice have increasingly relied on more structured forms of interaction, in which gamification incentives are employed to encourage users to make contributions (Jabr, Mookerjee, Tan, and Mookerjee 2014; Liu, Santhanam, and Webster 2017). Gamification takes elements from game designs to make tasks more engaging for users, within the context of online forums, to generate additional content (Liu, Santhanam, and Webster 2017; Goes, Guo, and Lin 2016).

Gamification: Many studies have reviewed the potential benefits of gamification (Jabr, Mookerjee, Tan, and Mookerjee 2014; Liu, Santhanam, and Webster 2017). For example, gamification has been shown to increase user contribution (Goes, Guo and Lin 2016; Cavusoglu et al. 2015), user retention (Moon and Sproull 2008), the quality of contributions (Moon and Sproull 2008), and user coordination (Forte et al. 2012). Although the benefits of gamification are well established, recent literature has sought to understand how the design of gamification fits the task for which it is intended. As motivated by the literature on task-technology fit (TTF), game design elements should match the intended purpose of a system (Goodhue 1995; Goodhue and Thompson 1995; Liu, Santhanam, and Webster 2017); further, in some environments gamification may be incongruent with the underlying task. We highlight certain gamification decisions that could affect its efficacy in certain types of environments.

For example, gamification often engenders competition among users (Morschheuser et al. 2016; Massung et al. 2013). For example, once someone responds to a question with the correct solution to a problem, others might be prevented from contributing. Thus, users are competing against one another to be one of the first to answer a question. However, although in some cases competition is desired or at least neutral, in others it might be desirable to obtain cooperation among users. This can be the case in particular when users need to work together to solve a problem.

Further, in some cases, the underlying task must be changed to enable gamification. For example, elements such as points or badges might not be suitable for work that lacks quantifiable performance measures (Liu, Santhanam, and Webster 2017).[2] For these reasons, settings with gamification might incentivize certain types of (quantifiable) effort over others or even restrict certain types of communication among users. For example, in a Q&A setting that rewards high-quality contributions (i.e., those that arise from high-quality questions and high-quality answers), users might be discouraged from posting comments that are not aligned with the central purpose of the platform and whose quality is difficult to measure objectively.

Many electronic networks of practice that employ gamification are characterized by asynchronous communication. One advantage of asynchronous postings is that they allow users additional time to compose messages (Dennis, Fuller, and Valacich 2008), a characteristic that may be particularly valuable in an environment in which messages are evaluated by other users. However, in some environments, synchronous communications may be preferred.

Synchronicity: One way to understand the effect of different communication methods on outcomes is with media synchronicity theory (MST), developed by Dennis et al. (2008). MST argues that communication has two primary properties: conveyance and convergence (Dennis et al. 2008; George, Carlson, and Valacich 2013). Conveyance focuses on the transmission of a diversity of information, while convergence focuses on clarifying the meaning of information that has already been exchanged or shared. Without convergence, users will not achieve a shared understanding. Convergence often requires rapid back-and-forth transmission of small quantities of information (Dennis et al. 2008; George, Carlson, and Valacich 2013), the type used in synchronous communication. MST argues that asynchronous communication such as asynchronous forums is preferred in conveyance processes. However, synchronous communication such as synchronous chat is better in convergence processes. Therefore, in an online Q&A forum, the transmission of messages through asynchronous forums may be appropriate in most cases to facilitate

[2] However, for a recent exception, see Burtch, He, Hong, and Lee (2020).

conveyance. However, in settings in which it is difficult to achieve a shared understanding—for example, when a question is unclear—synchronous communication may be particularly valuable.

The heterogeneous effects of synchronous and asynchronous communication tools have been examined within the context of online learning contexts (e.g., Coetzee, Fox, and Hartmann 2014; Johnson 2006; Rovai 2001; Oztok, Zingaro, Brett, and Hewitt 2013) and open source projects (Shihab et al. 2009; Elliott and Scacchi 2003). In those contexts, (synchronous) chat has been argued to provide faster responses to questions in Massive Open Online Courses (MOOCs) than (asynchronous) forums (Coetzee, Fox, Hearst, and Hartmann 2014) and help to resolve conflicts in open source software communities (Elliott and Scacchi 2003).

New communication methods can also bring about changes in the social structure of the community, which can affect productivity and shape user contribution behaviors (Singh, Tan and Mookerjee 2011; Singh, Tan and Youn 2011). These interactive environments can enhance network ties among users, which can have positive effects on complex knowledge exchange (Coleman 1988; Walker et al. 1997). Studies also show that people are more willing to share knowledge when there is mutual knowledge and the expectation of ongoing reciprocity (Athey and Ellison 2014), which may be more feasible in environments in which rapid communication is more feasible. For example, chat can encourage community building and help to facilitate the forming of relationships more effectively (than forums) (Coetzee, Fox, and Hartmann 2014; Rovai 2001). The role of free-form discussion in facilitating community building has been highlighted in prior research about online learning and educational technology (Johnson 2006; Branon and Essex 2001). For example, comparing synchronous and asynchronous discussion, Dede and Kremer (1999) note that asynchronous discussion enables richer exchange, but requires more time and engenders less social interaction than synchronous chat.

4.2. Implications for Performance on Stack Overflow

In the previous section, we discussed how two features, gamification and synchronicity of communications, might affect behavior in an electronic network of practice. To test these effects formally, we examine the implications of the introduction of a supportive channel, or “third space” (Oldenburg 1999; Steinkuehler and Williams 2006), for interactions in an electronic network of practice. Consistent with the goals of a third space to create an environment that promotes conversation and in which rank and status do not play a role, we examine the implications of the introduction of a new supportive channel that includes synchronous communications and in which gamification incentives do not play a role in user behavior. Our interest is the impact of third spaces on user behavior in general. However, the characteristics of a third space likely differ across electronic networks of practice. Given the presence of these differences and their impact on user behavior, rather than examine the implications of the introduction of a third space across multiple platforms, instead, we examine the implications in one particular environment, Stack Overflow.

In SO, the third space takes the form of a chat room (Stack Overflow 2020). Chat rooms in SO function like discussion boards found elsewhere, but with several differences from the traditional Q&A forum. First, users have no explicit incentives for posting in a chat room, unlike Stack Exchange Q&A forums, where they receive points for asking, answering, and editing questions and answers (among other things). That is, chat rooms offer no gamification incentives, but, at the same time, they have fewer explicit rules on what can be posted there. Lastly, communication in chat rooms occurs synchronously, with users responding immediately to one another’s posts.

As a result of synchronicity and the negligible role of gamification incentives, users may behave differently in chat rooms from a general Q&A site. These differences may mean that chat rooms have advantages for obtaining answers to certain types of questions. We focus on two particular differences: user reputation and question quality.

The SO Q&A site has well-established norms of behavior; as noted above, these norms help to facilitate gamification. Active community members have an interest in preserving the platform’s norms and might treat users who do not follow them in a hostile manner (Ford, Smith, Guo, and Parnin 2016, 2018; Valisescu, Capiluppo, and Serebrenik 2014). Moreover, newcomers might encounter barriers to learning these norms (Steinmacher et al. 2015). As a result, some users may decide not to ask or answer a question out of fear of negative feedback (Ford et al. 2016). In chat rooms, norms of behavior may be less well established, leading users to be less apprehensive about contributing. Moreover, given the more flexible and permissive behavioral norms that encourage users to contribute to the community, existing and experienced users may be able to mentor newcomers on behavioral norms to help them translate questions into a format that will elicit better answers from the community. These features may be particularly helpful in engaging with new users who are posting questions.

Gamification in the SO forum may encourage competition between users in ways that make it more difficult for certain types of question to be answered. Although SO offers a mechanism for adding comments to an answer, they cannot be threaded, and incentives are geared toward encouraging a user to be the first to answer a question (Bosu et al. 2013; Zagalskey et al. 2017). As a result, answers on SO are geared more toward the construction of "crowd" knowledge, which is not cumulative, as opposed to the construction of "participatory" knowledge, which involves a collaborative process of building upon prior knowledge (Zagalsky et al. 2017). The lack of threaded conversations and the incentives to be the first to answer may make it harder for the community to achieve a shared understanding of questions that are unclear or initially appear to be low quality. These questions are also more likely to be asked by new members of the community (Ahn et al. 2013).

As noted above, differences in communication patterns can engender differences in the network structure that can influence outcomes (Rice 1994; Butler 2001). First, in QA forums users interact under only one post whereas in chat rooms they can interact more frequently within a stream of posts. Therefore, they can form stronger social ties by communicating with one another in a chat environment. Stronger social ties can positively affect productivity in collective actions (Ren et al. 2007; Marwell and Oliver 1988; Krackhardt et al. 2003), such as responding to questions. Second, a chat room is often built by leading users and enables them to have social exchange with other users. It enhances individual centrality, the extent to which an individual is linked to others (Ahuja et al. 2003), for the leading users. This individual centrality can motivate leading users to contribute (Wasko and Faraj 2005; Grewal, Lilien and Mallaprogada 2006) and encourage other users in the subcommunity to contribute.

The synchronicity of chat rooms may also help to facilitate shared understanding between the question asker and answerer. Even if a question is answered online, the question asker may not be able to absorb the knowledge effectively (King and Lakhani 2011); some authors have argued that in the SO Q&A forum a certain level of experience is required to understand answers (Zagalsky et al 2017). That is, shared understanding or convergence may not be achieved. The synchronous communications available in chat rooms can facilitate convergence, particularly in environments in which a shared understanding is difficult to achieve, as when questions are unclear or asked by new users who have less understanding of the community norms.

In this section, we provide an overview of how chat rooms can facilitate the receipt of an earlier answer for questions that are posted on the SO Q&A site. However, the benefits of chat rooms are not equal across questions. Many questions receive a sufficient response after being posted on the Q&A site. We identified two conditions in which the value of chat rooms is likely to be high: questions that are asked by new users and those that are not clear.

Research Questions: In subsequent sections, we assess the salience of these observations for our data. In particular, *we examine whether, all other things equal, adding a discussion chat room will decrease the time it takes for related questions posted in the chat room to receive an accepted answer on the Q&A site*. Given the discussion above, we then explore heterogeneity in the treatment effect based on characteristics of the question asker and the question, *examining differences in the effects of adding a chat room on outcomes when the question asker is new to the community and when the question is low quality*. In the next section, we discuss our empirical approach to answering these questions.

5. Identification and Data Strategy

5.1 Identification of the Main Effect

We seek to understand how adding a question to the chat room affects the time that it takes for that question to receive an accepted answer on the SO Q&A site. We face an identification challenge because users push questions into a chat room for many different reasons. These questions might be harder to answer, or they might be more interesting, important, or more urgent, etc. Therefore, a direct comparison between the questions that are pushed into the chat rooms and those that are not might lead to selection bias in the results: For example, if users tend to push more difficult questions into chat rooms, which generally take longer to receive answers, the selection would lead to negative bias in our estimates of the effects of chat rooms.

To address potential identification concerns arising from a user-level choice to push questions into chat rooms, we exploit the feed function, which pushes questions into the chat rooms automatically and use a DID approach to identify the causal impact of moving a question into the chat room. Specifically, our primary estimation approach compares the outcomes of questions with tags that have been treated by the feed (i.e., a user has specified that all questions with this tag be pushed into a specific chat room) versus a comparison group of questions that have not been tagged in this way. Figure 2 illustrates examples of treated tags for which the associated chat rooms turned on the feed between October 2010 and December 2016, the period during which chat rooms and feeds were features that were incorporated into SO until the end of our sample period.

Our approach using treatment by the feed mitigates concerns about user-level selection on unobservables that might occur if we used user decisions to move questions into the chat room as our treatment. However, several things about our approach should be noted. First, feeds are turned on over time in our sample, so the treatment occurs over time (examples are shown in Figure 2). Second, the decision to turn on the feed is made by users of the chat rooms. Although we do not have specific evidence on the factors that shape user decisions to turn on the feed, it is possible that they are shaped by activity on the Q&A site, activity in the associated chat room, and the likelihood of receiving an answer with the associated tag on the Q&A site. If the trends in our treated tags are shaped by these factors in a way that is systemically different from those of the control tags, they have the potential to shape our results. To address this issue, we do two things. First, we use matching techniques to identify control tags with similar characteristics. Second, we focus on a short time window before and after the tag is treated by the feed, identifying the control group based on characteristics during this short period and examining the outcomes over this same period. This will mitigate concerns about differences in unobservable trends at the tag level that might shape our results.

We use propensity score matching (PSM) to identify control tags that are similar to the treated tags but that have not yet been treated. After identifying the control group, we construct a panel data set to run a DID regression. For each incidence of a treated tag in our data, we identify suitable control tags as described below and then include all questions from treated and control tags generated over a four-week time window in our sample: two weeks before and two weeks after the associated chat room turns on the feed. Our baseline empirical specification is as follows:

$$Y_{ijt} = \beta_0 + \beta_1 TurnOnFeed_{ijt} + \alpha_j + WeekDay_t + Week_t + \varepsilon_{ijt} \quad (1)$$

Y_{ijt} indicates the outcome variable of question i in tag j generated over time t. For treated tag j, $TurnOnFeed_{ijt} = 1$ when a chat room associated with tag j turns on the feed at time t and $TurnOnFeed_{ijt} = 0$ before and after the feed is turned on. For all control tags, $TurnOnFeed_{ijt} = 0$ during the four-week time window. We also include tag-level fixed effects α_j, weekly dummies ($Week_t$), and weekday dummies ($WeekDay_t$).

Our primary outcome variables Y_{ijt} denote whether the focal question receives an accepted answer within one, two, four, and eight hours. Thus, our outcome variable is a binary variable, and our estimation approach is a linear probability model. Our use of a linear probability model reflects several considerations. First, the linear probability model provides consistent estimates of the parameters of interest. A major concern is the existence of heteroskedastic standard errors, which we adjust for using robust standard errors. Second, the linear model allows for a more straightforward interpretation of the implied marginal effects from our parameter estimates. This is particularly the case when we explore heterogeneity in our treatment effect based on question and user characteristics, in which we interact the variable $TurnOnFeed_{ijt}$ with other variables: in these models, the interaction term in nonlinear models does not identify the partial cross-derivative (Ai and Norton 2003).

We estimate this regression using the within estimator. This method means that the calculated "within" R-squared values do not take into account the explanatory power of the fixed effects. Therefore, in our main results, we also estimated an equivalent, though computationally inefficient, "one-way fixed effects" estimator in order to calculate R-squared values that include the fixed effects.

5.2 Data

Our primary source of data is publicly available through the Stack Exchange API. We supplement the publicly available information with additional data scraped from chat.stackoverflow.com and user reputation data obtained through an agreement with SO.[3]

To assemble our data, we identify questions that are pushed into an associated chat room by a feed. We identify treated questions as those for which one chat room that is associated with a tag turns on a feed. We refer to a "tag episode" as a period in which a tag is treated by the feed. For example, Figure 2 lists six such tag episodes. Our data set consists of a set of tag episodes in addition to a set of control tags that are used in each tag episode. We next discuss our procedure for identifying tag episodes and their associated control tags.

As discussed above, our identification strategy requires that we use feeds that push *all* questions into the associated chat room without distinction. Our matching strategy also requires all treated tag units to have at least one week of activity in the associated chat room before the feed was turned on. From October 2010 to December 2016, we found 26 treated tag episodes that satisfy these criteria.[4] Each of these tags is unique except for python, which is treated twice in our data.[5]

The intensity of activity in chat rooms in SO shows great heterogeneity. Some tags have thousands of posts every week, while others go weeks at a time without activity. This heterogeneity creates problems for our estimation approach; chat rooms with very little activity are unlikely to influence the outcomes of questions that are pushed into them. To enable PSM to identify appropriate control tags, we restricted our sample to tags (control and treated) that are active for more than 80% of the observable weeks in our sample

[3] No user identities were revealed in this process.

[4] Of 73 tags for which a feed was activated, 24 applied selective filters, such as feeding only questions with bounties (extra reputational reward from the askers). An additional 23 started the feed within one week of the associated chat room's opening.

[5] The tag "python" has two associated chat rooms that turned on the feed function in January 2013 and September 2013, respectively. We include both episodes of treatment in our data.

period. This restriction was necessary to reduce heterogeneity across tags in the PSM procedure. Note, however, that the results are robust to using alternative cutoffs. We show the results using a 50% threshold in Appendix Tables A5 and A6. This procedure results in a data set that contains 18 treated tags and 1,012 potential control tag episodes before the PSM procedure is performed.

We then run a logit regression in which the unit of observation is a tag-week and in which the dependent variable is whether the tag is associated with a chat room that turns on the feed during the week. We use weekly aggregations of tag-level characteristics (question count, asker count, answer count, answerer count, and the number of answerers per question), chat room–level characteristics (message count, user count), lagged values (t-1) of those characteristics, and the weekly growth rate of the question count as matching covariates. We then use the estimated coefficients to calculate a propensity score for tag-week observations. For each treated tag, we calculated the difference between its propensity score in the week immediately before it is treated (days -7 to -1 prior to treatment) and the propensity score of all the potential control tags that are active in the same week.

For each treated tag episode, the PSM procedure pre-selected five control tags that have the closest squared difference in the propensity score. Among those suggestions, we dropped control tag-episodes that had no questions during the tag episode and eliminated duplicate uses of the same control tag during the same time period, as might happen if the same control tag was identified for two tags that were treated at the same time.[6] The final matched data set consists of 166,435 questions from 18 treated tag episodes and 83 control tag episodes. We observe treatment for 1,085 questions.

Tables 1 and 2 show the balance check on matching covariates after all these changes, before and after PSM. Appendix Table A1 describes each of the matching covariates, and Appendix Table A2 lists the results of the PSM model estimation. Before PSM, the differences in means between the treatment and control groups are insignificant, except for log(AnswerCount), log(AnswerCount(t-1)), and Answerer per

[6] For example, tag "java" was selected as a control tag for the treated tags "mercurial" and "c++". And because the treatment time for "mercurial" and "c++" was similar, the four-week time window of these two treated tags overlapped. So, we dropped "java" as a control tag for "c++".

question. Although the differences in means between the treatment and control groups are small even before PSM, we use control samples selected by PSM in our baseline regressions because the use of PSM in general reduces these differences even further. The main results remain robust to control tags that are not selected by PSM (Appendix Tables A3 and A4).

[Insert Table 1, Table 2 here]

Table 3 provides summary statistics for the outcome variables in our regressions. We focus on the time need to receive an accepted answer, rather than time needed to receive an answer because our analysis focuses on whether chat rooms facilitate the conveyance of an answer that addresses the question asker's need and for which the question asker and answerer have reached a shared understanding. Askers have an incentive to accept useful answers because the site offers a reputation reward for accepting an answer. 50.7% of questions receive an accepted answer within 8 hours (Accept8Hour) and only 9.9% (60.6%-50.7%) of questions receive an accepted answer after eight hours. So, we focus on the likelihood that a question will receive an accepted answer within one, two, four, and eight hours as our outcome variables.

We use the answer score to measure answer quality. The answer score is measured by the total upvotes minus downvotes that users on the platform (excluding the question asker him/herself) give the answer. It represents the collective evaluation of answers by users in the community (Burghardt et al. 2016). Because an accepted answer's score can be observed only for questions that have been given an accepted score, to incorporate the possibility that appearing in the chat room might change the distribution of quality across all answers, we also include the average score of all the answers for the focal question as an alternative measure of question quality.

[Insert Table 3 here]

6. Results

6.1 Main Effect of the Feed Function

Tables 4 and 5 present our main results. Table 4 shows that feeding a question to a chat room increases the likelihood of receiving an accepted answer within two, four, and eight hours. Column 2 shows that, after a question is fed to a chat room, the likelihood of getting an accepted answer within two hours increases by

3.2 percentage points, or 7% (0.032/0.46). The results for four hours and eight hours are qualitatively similar. However, although the point estimate for the effect of feeding a question on the likelihood of receiving an accepted answer in one hour is positive, it is smaller than for other time intervals and not statistically significant. We believe the insignificant result over the shorter time interval has several explanations. First, a short lag—less than one hour—often occurs between the time that a question is posed on the Q&A site and when it appears in a chat room. Second, even after the question appears in the chat room, it takes some time for answerers to view the question and come up with an answer and, then, for the asker to consider and accept a promising answer.

In Table 5, we examine the effects of treatment on the quality of answers. Our measurement of answer quality is based on the score of the answer. As noted above, this measure is commonly used for the quality of questions (Baltadzhieva and Chrupala 2015; Ravi et al. 2014; Arora et al. 2015). The average score of answers that are treated by the feed increases by 0.3, or 5.9% (Columns 2 and 4). However, this is likely driven by the increase in views received by questions that are treated by the feed; the number of question views increases by 17.7% (Column 5). Moreover, treatment by the feed neither increases nor decreases the score of the accepted answer (Columns 1 and 3). Note that the number of observations in these tables varies based on whether the question receives an answer or accepted answer.

Table 6 shows that the main results are driven by the tags associated with big chat rooms, which are more active. We define big chat rooms as those that have more than 140 messages per week. Column 2 shows that treatment has no effect (statistically or economically) on the likelihood of receiving an accepted answer in two hours to questions pushed into small chat rooms. In contrast, the likelihood of receiving an accepted answer within two hours to questions pushed into large chat rooms increases by 7.9 percentage points (relative to not being pushed into the chat room at all). Moreover, Column 1 shows that in big chat rooms, the feed significantly increases the likelihood of receiving an accepted answer even within one hour.

6.2 Robustness Checks

Our identification relies on the assumption that the waiting (lag) time until treated tag questions receive an accepted answer is similar to that for control tag questions except for the incidence of treatment. To explore the validity of this assumption, we include leads and lags to illustrate the difference in the trend (before and after the treatment, here called pre-trend and post-trend) between the control and treated tags.

We present the pre- and post-trend analysis in Table 7. We construct dummy variables for questions with treated tags, based on when, relative to the treatment, the question was asked. To construct pre-trend variables, we create dummy variables that equal one for questions affiliated with treated tags that were asked between six and four days before treatment (day -6 to day -4 in Table 7) and for questions asked between three days and one day before treatment (day -3 to day -1 in Table 7). We similarly construct dummy variables that equal one for treated questions based on the number of days after the initial switch in treatment status (i.e., the first day the questions with that tag began to be pushed into the chat room) that had elapsed by the time that the questions were asked.[7] The reference group consists of questions generated on days -7 to -14.

Our research design of using the feed to identify the effects of chat rooms provides a useful source of exogenous variation to identify our parameter estimates. However, because we use a fairly specific source of variation that exists for only a subset of questions, the statistical power for our pretrend analysis is limited. Only 1,085 questions were feeded in the post-period for 18 treated tag episodes, and the decomposition into days reduces the statistical power compared with that of our earlier results. The individual parameter estimates are identified from questions that are asked in each specific time window and, as noted earlier, for some tags, the treatment does not last for the entire post period.

Columns 1 to 4 show no evidence of a statistically significant effect from affiliation with a treated tag before treatment. Because of the statistical power issues mentioned above, the coefficients in the post period have economic significance but only weak statistical significance. However, as in the main results, the coefficients after treatment are still in the 3%-5% range.

Because of the differences in the results for questions pushed into big and small chat rooms shown in Table 6, Figure 3 presents a day-by-day pre-trend analysis for estimates using all chat rooms, big chat

[7] We dropped questions generated on the day that the feed is turned on because they can be either feeded questions (after the feed is on) or non-feeded questions (before the feed is on).

rooms only, and small chat rooms only. Figures 3(a) and 3(d) pool the estimates for big chat rooms and small chat rooms and, so, are consistent with Table 7, showing that the differences in the likelihood of receiving an accepted answer between treated and control tags are insignificant before the feed is turned on in the treated tags. When we divide the sample between big chat rooms (Figure 3(b) and 3(e)) and small chat rooms (Figure 3(c) and 3(f)), the results show no evidence of a pre-trend but evidence of a statistically and economically significant impact of being pushed into the chat rooms after treatment. However, as expected, the parameter estimates for small chat rooms are noisy and show little evidence of a discernible pattern before or after treatment.

Our identification strategy relies on comparing questions based on whether they are treated by the feed. However, questions may appear in chat rooms by other means as well. Users with a sufficient reputation can push questions into chat rooms directly, and other users may also push questions into chat rooms. In our main analysis, we include questions that are untreated by the feed but pushed into chat rooms by other means in our control group. In Table 8 they are included as a separate treated category. The results show that our main results from being treated by the feed remain unchanged. Further, although we cannot treat the estimates causally , the parameter estimates for the variables that indicate treatment by other means (by the asker or by the community) are interesting. In particular, questions that are pushed into chat rooms by askers are less likely to be answered, all other things being equal; these results might reflect selection on unobservables related to question quality.

We present two more robustness checks for the two samples in the Appendix. First, we analyze a "no PSM" sample, which compares the treated group to groups with questions from *all* control tags without any matching (Table A3, Table A4, and Figures A1(a) and (c)). Second, in the "50%" sample, we run the PSM logit using tags (control and treated) that are active for more than 50% of the observable weeks during our sample period, rather than 80% as in our baseline analysis (Table A5, Table A6, and Figures A1(b) and (d)). The main results and the pre-trend analysis are both robust when we use these alternative samples.

6.3 Heterogeneous Effect of the Feed

In Section 4, we discussed how the effect of chat rooms might be greater on particular types of users and questions that might be less likely to receive an answer on the Q&A site. In particular, we discussed whether chat rooms could disproportionately influence outcomes for questions asked by low-reputation users and questions that are lower in quality. In this section, we examine whether the empirical evidence is consistent with these assertions.

First, in Table 9, we investigate heterogeneity in the effects of chat rooms based on the reputation of users. We obtained reputation data from SO and constructed a variable that indicates questions posed by users with a reputation that is 0 or negative, *LowRep*.[8] We similarly create a variable that indicates whether users have a reputation of more than 0, *HighRep*. We interact both variables with the treatment variable *TurnOnFeed.* In this sample, we dropped 12,146 questions that are from users who have no recorded reputation (e.g., users who deleted their SO account). Moreover, to keep the sample consistent with the results in Tables 10 and 11, we also dropped 360 questions for which we cannot calculate the question quality (because they were later deleted by users). We checked the baseline specification for this sample, and the results (see Appendix Table A7) are consistent with those in Table 4.

The questions of users with a reputation of 0 are less likely to receive an accepted answer. For example, in column 2, the coefficient on *HighRep* is 0.1458, indicating that users with a reputation of zero or less are 14.6 percentage points less likely to receive an accepted answer in two hours (31.9% = 0.1458/0.4567). However, this asymmetry of the forum is mitigated by the chat room, which significantly increases the probability of receiving an accepted answer for users with a reputation of 0 or less but does not influence outcomes for users with a positive reputation. For example, whereas in column 2, we estimate that positive reputation users are 14.6 percentage points more likely than other users to receive an accepted answer within two hours, this difference is estimated at only 10.4 percentage points (= 0.1458 + 0.0179 – 0.0594) when the chat room function is turned on. The results in Table 9 are robust to using a different threshold to identify low reputation (low reputation is equal to one when reputation is lower than the 20^{th} percentile relative to all users, rather than reputation <= 0; the results are in Appendix Table A8) and are

[8] The reputational score of users declines if they receive down votes on answers or questions.

also robust to controlling for a question's quality (see Table A9).

In Table 10, we analyze whether chat rooms can help users to devise solutions to questions that are difficult to understand. Following prior literature (Ignatova et al. 2008; Agichtein et al. 2008; Liu et al. 2008), we measure question quality based on the incidence of misspelled words. We did not choose nontextual features, such as the score of questions and the number of edits by other users, because they might be affected by treatment. We use Hunspell (Wikipedia 2017) to identify misspelled words in questions and calculate the percentage of misspelled words (number of misspelled words/number of total words) to measure question quality.[9]

As before, we create separate variables for low-quality and high-quality questions. Low-quality questions are defined as those whose quality is lower than the bottom 25th percentile (*LowQuality*), and high-quality questions are defined as those whose quality is higher than the bottom 25th percentile (*HighQuality*). Table 10 shows that low-quality questions are generally less likely to receive any answers. For example, in column 2, low-quality questions are 2.0 percentage points (4.3% = 0.0197/0.4567) less likely to be answered than other questions. Moreover, unlike high-quality questions, low-quality questions do not benefit from being forwarded to a chat room. Instead, the coefficient estimate of chat rooms for such low-quality questions cannot be differentiated from zero.

In Section 4, we asserted that chat rooms have a stronger effect on the time to the receipt of an accepted answer to questions that are unclear. Thus, these results are inconsistent with that assertion. Although chat rooms may improve convergence around questions that are difficult to understand, these questions are also harder to answer on average, and, so, users might still choose not to answer them even in the chat room. Because the propensity of potential answerers to attempt to answer these questions might differ for questions posed by new and experienced users, in our next analysis, we examine the joint effects of user reputation, question quality, and their interaction.

In Table 11, we combine question quality and user reputation into a single specification with a

[9] Details are available at https://hunspell.github.io.

three-way interaction so that we can present all the puzzle pieces in one consolidated picture. To do so, we include three dummies in the table to indicate when the feed was turned on (*TurnOnFeed*), whether a question is of low quality (*LowQuality*), and whether the question asker is inexperienced (*LowRep*). Moreover, we included all bilateral interactions and a three-way interaction term to disentangle the interplay of quality and reputation when analyzing how chat rooms affect inexperienced users. Unlike in the prior tables, to simplify exposition, we do not include the counterpart of these conditions (*HighQuality* and *HighRep*); however, Table 11 directly shows the marginal effect of being exposed to the feed under different conditions. The underlying specification of this regression is:

$$Y_{ijt} = \beta_0 + \beta_1 TurnOnFeed_{ijt} + \beta_2 LowRep_{ijt} + \beta_3 LowQuality_{ijt} + \beta_{32} LowQuality_{ijt} * LowRep_{ijt} + \beta_{31} LowQuality_{ijt} * TurnOnFeed_{ijt} + \beta_{12} TurnOnFeed_{ijt} * LowRep_{ijt} + \beta_{123} TurnOnFeed_{ijt} * LowRep_{ijt} * LowQuality_{ijt} + \alpha_j + WeekDay_t + Week_t + \varepsilon_{ijt} \quad (2)$$

In this specification Y_{ijt} is the outcome variable of question i in tag j generated at time t. $TurnOnFeed_{ijt}$ indicates whether question i was pushed into the chat room by the feed function at time t. $LowRep_{ijt}$ indicates whether the reputation of the asker of question i is 0 or below. $LowQuality_{ijt}$ indicates whether the quality of question i is below the 25th percentile. We also include tag-chat-level fixed effects α_j, weekly dummies ($Week_t$), and weekday dummies ($WeekDay_t$). Table 11 shows the regression results of estimating equation (2).

Table 12 lists the marginal effects under different combinations of user reputation and question quality for the dependent variable *Accept2Hour.* Additional marginal effect calculations are in Appendix Table A10. For simplicity, we focus our discussion on the results in column 2 (*Accept2Hour*) and the accompanying discussion in Table 12, though other results are similar.

The main coefficient on *TurnOnFeed* (which identifies the effects of the feed for high-quality questions asked by high-reputation users) is similar to the estimates in the main specification (0.0426), but the interaction with *LowQuality* (-0.1097) suggests that the feed does not increase the likelihood that questions of low quality will receive an accepted answer. In fact, the results suggest that the effects of the feed on low-quality questions are negative for high-reputation users (the marginal effect is -0.0671)[10] and statistically significant at the 10% level, although over longer time windows, this result becomes weaker both statistically and economically.

Our main focus is the coefficient of the three-way interaction, which is estimated to be significantly positive and large (0.1788). The marginal effect of the feed for inexperienced users is greater for low-quality questions that are asked by low-reputation users. This finding is remarkable, especially against the backdrop of the negative coefficients for inexperienced users (in general) and for low-quality questions (in chat rooms). We explore the nuances of this result in several ways.

The changes in the likelihood that low-reputation users in the Q&A forum will receive an answer and when the questions are pushed into the chat room are particularly informative. On the Q&A site (i.e., excluding the effects of the feed), low-reputation users (*LowRep*) asking low-quality questions (*LowQuality*) are 17.6 percentage points less likely to receive an answer in two hours than high-reputation users with high-quality questions when questions are not pushed into the chat room.[11] This changes only slightly, to only 13.6 percentage points less likely to be answered, when low-reputation users ask high-quality questions. However, chat rooms help to mitigate these effects. Low-reputation users asking low-quality questions experience the greatest benefits when questions are posted in the chat room (an increase of 10.8 percentage points),[12] much more than when low-reputation users ask high-quality questions (an increase of 3.9 percentage points).[13] This helps in part to offset the disadvantages of being a low-reputation user on SO. In this context, the positive coefficient on the three-way interaction highlights that chat rooms are helpful for inexperienced users when they ask low-quality questions and demonstrate more tolerance of low-quality questions when they come from inexperienced users. In contrast, high-reputation users receive few benefits when their questions are posted in a chat room.

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[10] This can be seen by adding up the coefficients: 0.0426 – 0.1097 = -0.0671.
[11] This can be seen by adding up the coefficients: - 0.1360 – 0.0070 - 0.0329= -0.176.
[12] This can be seen by adding up the coefficients: 0.0426 – 0.0041– 0.1097 + 0.1788 = 0.1076.
[13] This can be seen by adding up the coefficients: 0.0426 – 0.0041 = 0.0385.

7. Discussion and Conclusions

We examine whether an informal new channel for communication can improve the efficiency of knowledge transfer in a network of practice. We analyze this question using the chat room functionality in the well-known Q&A forum Stack Overflow. We identify the causal effect of chat rooms by exploiting a feed function, which nonselectively pushed all questions from the Q&A forum into the relevant chat rooms that use this feature. We report two main findings. First, the adoption of a chat room reduces the time it takes for a question in the main Q&A forum to receive a satisfactory answer. The second channel thus increases the efficiency of the forum, and it does so without any negative effects on answer quality. Second, we show that chat rooms disproportionately benefit certain user groups and certain types of questions. Specifically, inexperienced users who asked low quality questions benefited most from the chat room.

This paper has several limitations. First, our primary identification strategy relies on the feed function that pushed questions into the chat rooms. This means that our identification is based on a relatively small number of questions pushed into chat rooms by a feed. However, questions may appear in chat rooms by other means. Users can push questions into chat rooms directly, and other users may also push questions into chat rooms. Although we document that questions are more likely to benefit when they are pushed into the chat room by users other than the person who originally posed them, we cannot draw causal inferences about these questions, because they might reflect selection on unobservables, such as questions that are difficult to answer.

Our identification strategy requires that questions associated with tags that are treated by the feed do not change over time in ways that are different from those in the control group generated by our propensity score estimator. To generate a valid control group, we use PSM. Although balance checks support this approach, and our main findings are unchanged if we use all tags, as with any matching estimator, this matching strategy represents a particular specification choice.

Our findings have important managerial implications. In particular, our results regarding low-reputation users and low-quality questions showed that the chat room provides the structured main channel of the network of practice with a “friendlier space,” which can facilitate newcomers’ entry into the community. These findings suggest that opening a third space such as chat rooms can be an effective managerial tool for supporting the main community by partially addressing inefficiencies in knowledge sharing as well as improving conditions for new users. A third space can thus mitigate inequality in access to community knowledge that might arise from employing efficiency-enhancing mechanisms, such as gamification, on the main channel. Hence, incorporating a third space into the network of practice might be an attractive option for managers who are considering the use of efficiency-enhancing mechanisms but are concerned about the impact of including inexperienced users.

Our research contributes to a growing literature on understanding platform decisions in online communities of practice. However, we depart from existing literature in important ways by focusing on a phenomenon that is growing in importance in these communities yet remains underexplored in existing literature: the creation and emergence of a third space. Our research represents a first step in addressing these issues, but many questions remain. Further research should examine the robustness of our results to other communities that have introduced third spaces, such as Wikipedia, and explore the characteristics of these spaces that most effectively improve outcomes. Further, our work focuses on identifying the effects of the treatment on the treated, namely, sites that have introduced chat rooms. Future research should investigate how the introduction of these spaces affects other parts of the community that are untreated. We hope our research spurs additional work in this important area.

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Tables and Figures

Figure 1a

Figure 1b

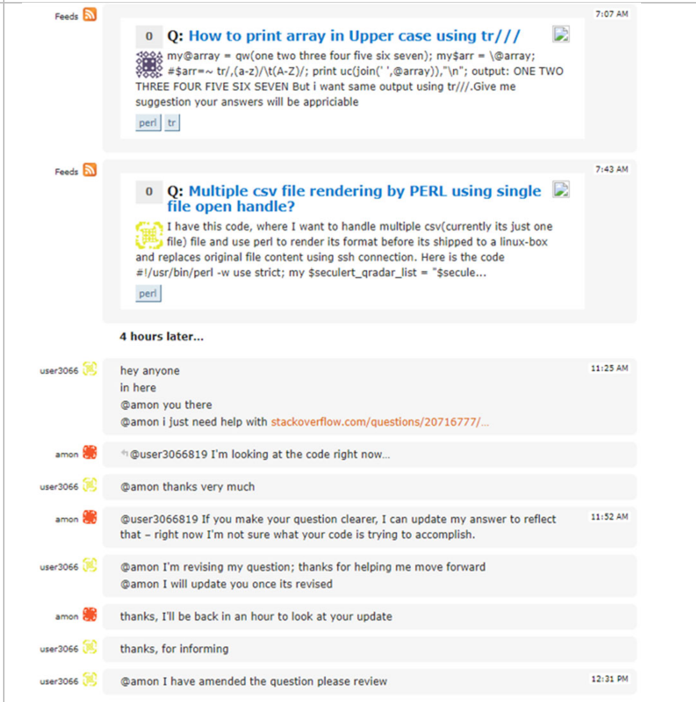


Figure 1. Discussing a question in chat rooms

Figure 2. Time line of turning on the feed function

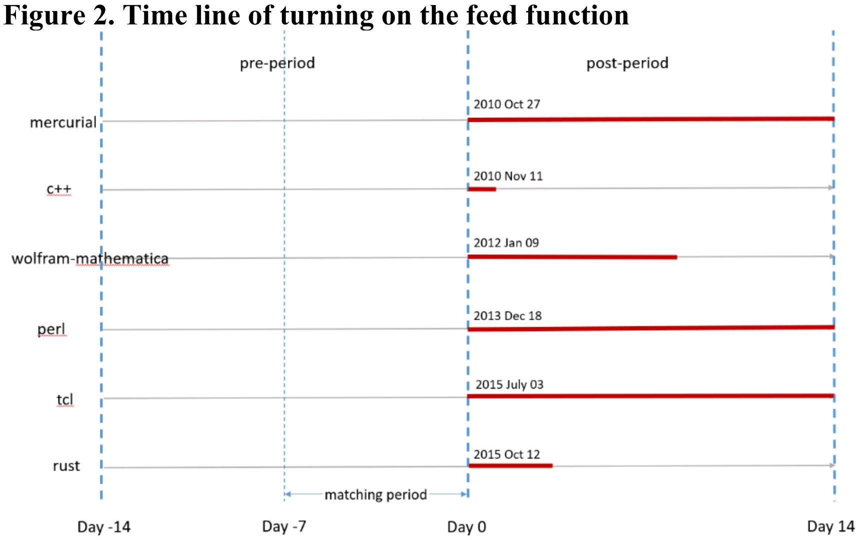


Table 1. Balance check before PSM

	treat	control	Difference	se	(*p*-value)
Estimated propensity score	0.03	0.01	0.02	0.01	0.00
log(QuestionCount)	4.90	4.23	0.67	0.44	0.13
log(AskerCount)	4.69	4.10	0.59	0.43	0.17
log(AnswerCount)	5.90	4.99	0.92	0.52	0.08
log(AnswererCount)	4.55	4.08	0.47	0.43	0.27
log(MessageCount)	3.74	3.43	0.32	0.58	0.59
log(UserCount)	1.63	1.57	0.05	0.27	0.84
log(QuestionCount(t-1))	4.92	4.21	0.72	0.45	0.11
log(AskerCount(t-1))	4.72	4.08	0.64	0.44	0.14
log(AnswerCount(t-1))	6.00	4.97	1.03	0.53	0.05
log(AnswererCount(t-1))	4.60	4.06	0.54	0.44	0.22
log(MessageCount(t-1))	3.25	3.61	-0.36	0.55	0.51
log(UserCount(t-1))	1.47	1.65	-0.19	0.26	0.47
GrowthRate	-0.00	0.09	-0.10	0.12	0.43
Answerer per question	0.73	0.92	-0.19	0.10	0.05
N. of tag episode	18	1008			

Note: The column "treat" represents the average value of variables in the first column across treated tag-episodes in the week before turning on the feed (matching period), and the column "control" represents the average value of variables in the first column across control tag-episodes in the week before turning on the feed (matching period). The column "Difference" represents the sample difference between treated tag-episodes and control tag-episodes.

Table 2. Balance check after PSM

	treat	control	Difference	se	(p-value)
Estimated propensity score	0.03	0.01	0.02	0.01	0.06
log(QuestionCount)	4.90	4.46	0.43	0.54	0.42
log(AskerCount)	4.69	4.33	0.36	0.52	0.49
log(AnswerCount)	5.90	5.59	0.31	0.59	0.60
log(AnswererCount)	4.55	4.44	0.11	0.49	0.83
log(MessageCount)	3.74	3.85	-0.11	0.59	0.85
log(UserCount)	1.63	1.73	-0.11	0.27	0.69
log(QuestionCount(t-1))	4.92	4.49	0.43	0.53	0.42
log(AskerCount(t-1))	4.72	4.36	0.36	0.51	0.48
log(AnswerCount(t-1))	6.00	5.54	0.46	0.60	0.44
log(AnswererCount(t-1))	4.60	4.42	0.18	0.50	0.72
log(MessageCount(t-1))	3.25	4.02	-0.77	0.57	0.19
log(UserCount(t-1))	1.47	1.88	-0.42	0.27	0.12
GrowthRate	-0.00	0.01	-0.01	0.08	0.85
Answerer per question	0.73	1.10	-0.37	0.13	0.01
N. of tag episode	18	83			

Note: The column "treat" represents the average value of variables in the first column across treated tag-episodes in the week before turning on the feed (matching period), and the column "control" represents the average value of variables in the first column across control tag-episodes in the week before turning on the feed (matching period). The column "Difference" represents the sample difference between treated tag-episodes and control tag-episodes.

Table 3. Summary statistics

	N	Mean	St. Dev.	Min.	Max.
AcceptHour	166435	0.4133	0.4924	0	1
Accept2Hour	166435	0.4555	0.4980	0	1
Accept4Hour	166435	0.4855	0.4998	0	1
Accept8Hour	166435	0.5068	0.5000	0	1
Accept	166435	0.6061	0.4886	0	1
AcceptScore	100869	4.6288	19.4837	-20	1983
AveScore	153935	2.1364	5.4402	-7	362.50
log(AcceptScore)	81687	0.9624	0.9814	0	7.5924
log(AveScore)	113827	0.5236	0.9111	-2.1972	5.8930
log(ViewCount)	166435	6.3480	1.6643	1.9459	14.6153

Table 4. The effect of chat rooms on the efficiency of knowledge exchange

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed	0.0174	0.0320**	0.0259**	0.0335**
	(0.0107)	(0.0144)	(0.0120)	(0.0132)
R^2-within	0.0007	0.0007	0.0007	0.0007
R^2-total	0.0295	0.0286	0.0283	0.0286
N	166,435	166,435	166,435	166,435
N. of tag-episode	101	101	101	101
Mean	0.41	0.46	0.49	0.51

* *p*<0.1; ** *p*<0.05; *** *p*<0.01. Heteroskedasticity robust standard error clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table 5. The effect of the chat rooms on answer quality

	AcceptScore (1)	AveScore (2)	ln(AcceptScore) (3)	lnAveScore (4)	ln(ViewCount) (5)
TurnOnFeed	0.0099	0.3067**	0.0401	0.0572*	0.1634***
	(0.4458)	(0.1217)	(0.0316)	(0.0292)	(0.0617)
R^2-within	0.0007	0.0007	0.0007	0.0007	0.0006
R^2-total	0.0130	0.0236	0.0540	0.0483	0.1101
N	100,869	153,935	81,687	113,827	166,435
N. of tag-episode	101	101	101	101	101
Mean	4.63	2.14	0.96	0.52	6.35

* p<0.1; ** p<0.05; *** p<0.01. Heteroskedasticity robust standard error clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table 6. Big chat rooms benefit more from the feed function

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed*smallChat	-0.0043	0.0043	0.0044	0.0140
	(0.0161)	(0.0152)	(0.0129)	(0.0147)
TurnOnFeed*bigChat	0.0542***	0.0791**	0.0622***	0.0664***
	(0.0166)	(0.0307)	(0.0201)	(0.0249)
R^2-within	0.0007	0.0007	0.0007	0.0007
R^2-total	0.0295	0.0286	0.0284	0.0286
N	166,435	166,435	166,435	166,435
N. of tag-episode	101	101	101	101
Diff: bigChat -smallChat	0.0585**	0.0748**	0.0577**	0.0525*
	(0.0231)	(0.0342)	(0.0238)	(0.0289)
Mean	0.41	0.46	0.49	0.51

* p<0.1; ** p<0.05; *** p<0.01. Heteroskedasticity robust standard error clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table 7. Pre-trend analysis

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
Treat*(Day -6 to -4)	0.0012	0.0026	0.0064	0.0105
	(0.0101)	(0.0110)	(0.0120)	(0.0095)
Treat*(Day -3 to -1)	0.0109	0.0104	0.0090	0.0095
	(0.0079)	(0.0084)	(0.0088)	(0.0090)
TurnOnFeed * (Day 1 to 3)	0.0157	0.0335	0.0269	0.0489
	(0.0477)	(0.0416)	(0.0493)	(0.0507)
TurnOnFeed * (Day 4 to 6)	0.0290	0.0412	0.0378*	0.0479***
	(0.0218)	(0.0251)	(0.0206)	(0.0181)
TurnOnFeed * (After day 6)	0.0170	0.0192	0.0109	0.0182
	(0.0253)	(0.0252)	(0.0258)	(0.0296)
R^2-within	0.0007	0.0007	0.0007	0.0007
R^2-total	0.0295	0.0286	0.0284	0.0286
N	165,784	165,784	165,784	165,784
N. of tag-episode	101	101	101	101
Mean	0.41	0.46	0.49	0.51

* p<0.1; ** p<0.05; *** p<0.01. Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Figure 3. Estimated impact of chat rooms on the likelihood of receiving an accepted answer within 2 hours and 4 hours

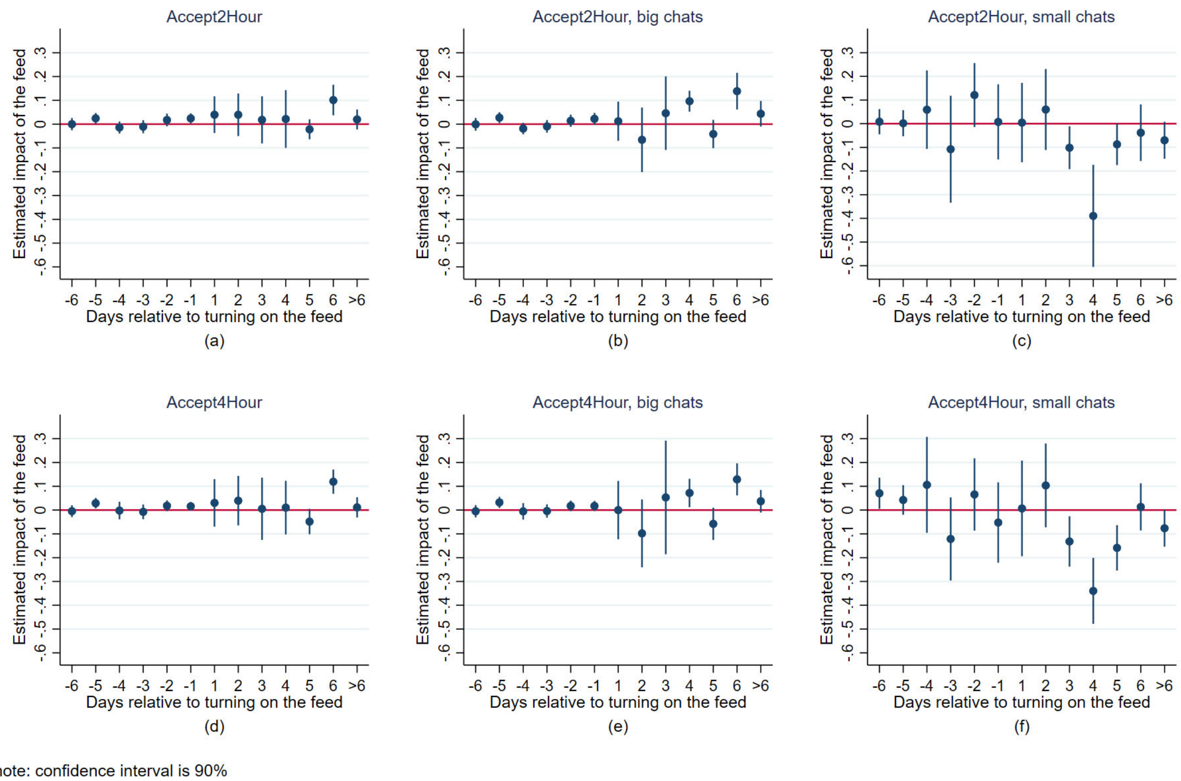


Table 8. Robustness check: Control for questions treated by askers and other users

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed	0.0233**	0.0384**	0.0268**	0.0318**
	(0.0108)	(0.0147)	(0.0124)	(0.0142)
treatasker	-0.1164***	-0.1060***	-0.0873***	-0.0901***
	(0.0198)	(0.0245)	(0.0264)	(0.0284)
treatother	0.0590***	0.0625***	0.0607***	0.0630***
	(0.0119)	(0.0122)	(0.0136)	(0.0134)
R^2	0.0010	0.0010	0.0009	0.0010
N	166,435	166,435	166,435	166,435
N. of tag-episode	101	101	101	101
Mean	0.41	0.46	0.49	0.51

* p<0.1; ** p<0.05; *** p<0.01. Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table 9. Low-reputation users benefit more from the chat rooms

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed*LowRep	0.0511***	0.0594**	0.0647**	0.0661**
	(0.0183)	(0.0252)	(0.0323)	(0.0306)
TurnOnFeed*HighRep	-0.0013	0.0179	0.0085	0.0187
	(0.0128)	(0.0157)	(0.0132)	(0.0159)
HighRep	0.1331***	0.1458***	0.1547***	0.1620***
	(0.0091)	(0.0094)	(0.0099)	(0.0102)
R^2	0.0125	0.0146	0.0162	0.0178
N	153,929	153,929	153,929	153,929
N. of tag-episode	93	93	93	93
Diff (marginal): HighRep – LowRep	-0.0525***	-0.0415	-0.0563	-0.0474
	(0.0188)	(0.0276)	(0.0383)	(0.0385)
Diff (total): HighRep - LowRep	0.1037***	0.1043***	0.1055***	0.1061***
	(0.0258)	(0.0258)	(0.0257)	(0.0258)
Mean	0.4147	0.4567	0.4868	0.5081

* p<0.1; ** p<0.05; *** p<0.01. Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table 10. Questions with lower quality benefit less from the chat rooms

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed*HighQuality	0.0254**	0.0476***	0.0418***	0.0395***
	(0.0116)	(0.0146)	(0.0110)	(0.0131)
TurnOnFeed*LowQuality	-0.0258	-0.0220	-0.0305	0.0134
	(0.0258)	(0.0269)	(0.0284)	(0.0279)
LowQuality	-0.0173***	-0.0197***	-0.0199***	-0.0213***
	(0.0054)	(0.0051)	(0.0052)	(0.0051)
R^2	0.0010	0.0011	0.0011	0.0012
N	153,929	153,929	153,929	153,929
N. of tag-episode	93	93	93	93
Diff: LowQuality - HighQuality	-0.0512*	-0.0695***	-0.0723**	-0.0261
	(0.0268)	(0.0254)	(0.0289)	(0.0262)
Mean	0.4147	0.4567	0.4868	0.5081

* p<0.1; ** p<0.05; *** p<0.01. Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table 11. Three-way interaction

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed	0.0193	0.0426**	0.0309**	0.0302*
	(0.0137)	(0.0165)	(0.0122)	(0.0162)
TurnOnFeed*LowRep	0.0061	-0.0041	0.0267	0.0155
	(0.0225)	(0.0283)	(0.0393)	(0.0441)
TurnOnFeed*LowRep*LowQuality	0.1769***	0.1788***	0.1234*	0.1204*
	(0.0450)	(0.0633)	(0.0626)	(0.0622)
LowQuality*LowRep	-0.0296***	-0.0329***	-0.0336***	-0.0336***
	(0.0082)	(0.0094)	(0.0090)	(0.0093)
TurnOnFeed * LowQuality	-0.0917***	-0.1097***	-0.1004***	-0.0528
	(0.0318)	(0.0365)	(0.0376)	(0.0393)
LowQuality	-0.0058	-0.0070	-0.0067	-0.0078
	(0.0050)	(0.0050)	(0.0050)	(0.0049)
LowRep	-0.1243***	-0.1360***	-0.1447***	-0.1520***
	(0.0095)	(0.0098)	(0.0105)	(0.0110)
R^2	0.0128	0.0150	0.0166	0.0181
N	153,929	153,929	153,929	153,929
N. of tag-episode	93	93	93	93
Mean	0.4147	0.4567	0.4868	0.5081

* p<0.1; ** p<0.05; *** p<0.01. Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table 12. Effect of the feed on the likelihood for receiving an answer within two hours for different levels of reputation and quality

Panel A: Marginal Effects of the Feed		
	Low-reputation	High reputation
Low quality	0.1076	-0.0671
High quality	0.0385	0.0426
Panel B: Relative likelihood of receiving an answer within 2 hours for questions that are not treated by the feed		
	Low reputation	High reputation
Low quality	-0.1759	-0.0070
High quality	-0.1360	0
Panel C: Total relative magnitude of likelihood of receiving an answer within 2 hours if pushed into chat room		
	Low reputation	High reputation
Low quality	-0.0683	-0.0741
High quality	-0.0975	0.0426
Panel D: Total probability of receiving an answer within 2 hours if pushed into chat room		
	Low reputation	High reputation
Low quality	0.389	0.383
High quality	0.359	0.500

Notes: The table analyzes the effect of the feed on the likelihood of receiving an answer (within 2 hours) for questions with different combinations of reputation and quality. Panel A shows the marginal effects of the feed and its difference based on reputation and quality. Panel B shows the likelihood that a question will be answered based on quality and reputation if it is not treated by the feed. Panel C summarizes panels A and B by combining their effects to show the total relative magnitudes of the likelihood that a question will receive an answer within 2 hours when pushed into a chat room. Panel D sums up the effects in Panel C with the average likelihood that a question will receive an answer in the Q&A forum. More details on marginal effects for other dependent variables are provided in Appendix Table A10.

Appendix

Table A1. PSM: matching covariates

log(QuestionCount)	Log of question count under associated tag in each week
log(AskerCount)	Log of asker count under associated tag in each week
log(AnswerCount)	Log of answer count under associated tag in each week
log(AnswererCount)	Log of answerer count under associated tag in each week
log(MessageCount)	Log of message count under associated chat room in each week
log(UserCount)	Log of unique users count under associated chat room in each week
log(QuestionCount(t-1))	Log of question count under associated tag in the previous week
log(AskerCount(t-1))	Log of asker count under associated tag in the previous week
log(AnswerCount(t-1))	Log of answer count under associated tag in the previous week
log(AnswererCount(t-1))	Log of answerer count under associated tag in the previous week
log(MessageCount(t-1))	Log of message count under associated chat room in the previous week
log(UserCount(t-1))	Log of unique users count under associated chat room in the previous week
GrowthRate	Growth rate in question count by week
Answerer per question	Number of answerers per question

Table A2. PSM: logit regression

	TurnOnFeed
log(QuestionCount)	-4.9149***
	(1.1889)
log(AskerCount)	3.8173***
	(1.1232)
log(AnswerCount)	2.4174***
	(0.2622)
log(AnswererCount)	-1.9448***
	(0.5124)
log(MessageCount)	0.6104***
	(0.0937)
log(UserCount)	-1.4057***
	(0.2927)
log(QuestionCount(t-1))	-4.6931***
	(1.0580)
log(AskerCount(t-1))	4.3533***
	(1.1108)
log(AnswerCount(t-1))	2.4208***
	(0.2551)
log(AnswererCount(t-1))	-2.4967***
	(0.4451)
log(MessageCount(t-1))	0.3385***
	(0.0939)
log(UserCount(t-1))	-0.6666**
	(0.2904)
GrowthRate	0.0020
	(0.0039)
Answerer per question	-0.2738
	(0.2731)
Pseudo R^2	0.3290
N. of tag-weeks	46,528

Notes: No. of treated tags = 18; No. of treated tags = 706; Robust standard error in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A3. Robustness: Effect of chat rooms on the efficiency of knowledge exchange (before PSM)

	AcceptHour	Accept2Hour	Accept4Hour	Accept8Hour
	(1)	(2)	(3)	(4)
TurnOnFeed	0.0218**	0.0332***	0.0273***	0.0361***
	(0.0108)	(0.0108)	(0.0081)	(0.0094)
R^2	0.0002	0.0002	0.0002	0.0002
N	1,097,468	1,097,468	1,097,468	1,097,468
N. of tag-episode	1,026	1,026	1,026	1,026
Mean	0.39	0.43	0.46	0.48

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

We keep tag episodes that have observations in matching covariates for at least 80% of the weeks and include all 1,012 tags without selecting on control tags by PSM. The final sample includes 18 treated tags and 1,008 control tags because 4 control tags did not have questions during the four-week time window.

Table A4. Robustness: Effect of chat rooms on answer quality (before PSM)

	AcceptScore	aveScore	Ln(AcceptScore)	Ln(AveScore)	Ln(ViewCount)
	(1)	(2)	(3)	(4)	(5)
TurnOnFeed	-0.2049	0.2147**	0.0358	0.0632**	0.1261**
	(0.3334)	(0.1039)	(0.0281)	(0.0268)	(0.0570)
R^2	0.0002	0.0002	0.0006	0.0004	0.0006
N	639,621	995,547	504,446	703,975	1,097,468
N. of tag-episode	1,024	1,026	1,022	1,025	1,026
Mean	3.77	1.84	0.86	0.46	6.11

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

We keep tags that have observations in matching covariates for at least 80% of the weeks and include all 1,012 tags without selecting on control tags by PSM. The final sample includes 18 treated tags and 1,008 control tags because 4 control tags did not have questions during the four-week time window.

Table A5. Robustness: Effect of chat rooms on efficiency of knowledge exchange (50% active chat rooms)

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed	0.0177*	0.0299**	0.0233***	0.0315***
	(0.0101)	(0.0114)	(0.0088)	(0.0109)
R^2	0.0009	0.0009	0.0009	0.0010
N	140,629	140,629	140,629	140,629
N. of tag-episode	103	103	103	103
Mean	0.43	0.47	0.50	0.52

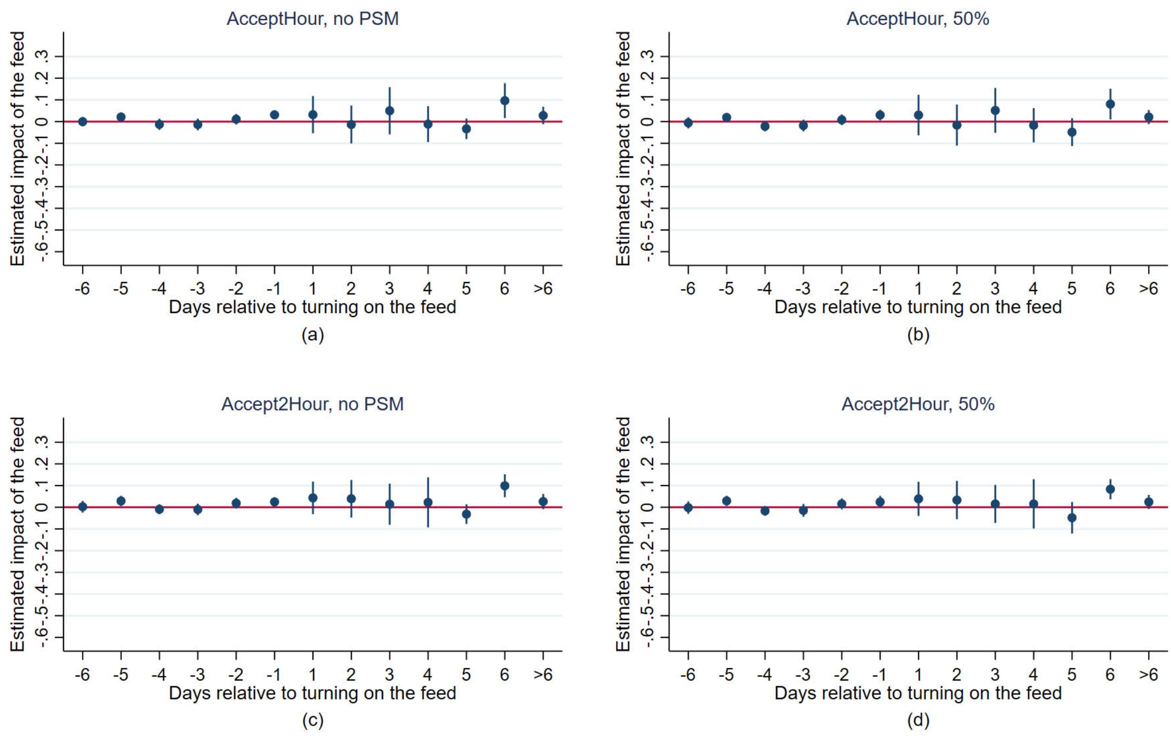
* p<0.1; ** p<0.05; *** p<0.01
Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.
We keep tags that have observations in matching covariates for at least 50% of the weeks and include tags selected by PSM. The sample includes 19 treated tags and 84 control tags.

Table A6. Robustness: Effect of chat rooms on answer quality (50% active chat rooms)

	AcceptScore (1)	aveScore (2)	Ln(AcceptScore) (3)	Ln(AveScore) (4)	Ln(ViewCount) (5)
TurnOnFeed	-0.0142	0.1692	0.0415	0.0433	0.1538**
	(0.5219)	(0.1750)	(0.0300)	(0.0299)	(0.0590)
R^2	0.0008	0.0008	0.0012	0.0012	0.0009
N	88,327	131,835	72,858	100,584	140,629
N. of tag-episode	102	102	102	102	103
Mean	5.01	2.31	1.02	0.56	6.51

* p<0.1; ** p<0.05; *** p<0.01
Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.
We keep tags that have observations in matching covariates for at least 50% of the weeks and include tags selected by PSM. The sample includes 19 treated tags and 84 control tags.

Figure A1. Robustness check: The estimated impact of the chat rooms on the likelihood of getting an accepted answer within 2 hours and 4 hours



note: confidence interval is 90%

Table A7. Main effect on heterogeneity analysis sample: user with reputation record and questions with quality measure

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed	0.0132	0.0310**	0.0247**	0.0335**
	(0.0117)	(0.0150)	(0.0120)	(0.0141)
R^2	0.0007	0.0008	0.0007	0.0008
N	153,929	153,929	153,929	153,929
N. of tag-episode	93	93	93	93
Mean	0.41	0.46	0.49	0.51

* *p*<0.1; ** *p*<0.05; *** *p*<0.01
Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table A8. Low-reputation users benefit more from the chat rooms: alternative threshold for low reputation.

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed*repaboveBottom20	-0.0006	0.0185	0.0091	0.0193
	(0.0129)	(0.0158)	(0.0132)	(0.0160)
TurnOnFeed*repBottom20	0.0474***	0.0560**	0.0612*	0.0627**
	(0.0180)	(0.0250)	(0.0322)	(0.0304)
repBottom20	-0.1286***	-0.1416***	-0.1505***	-0.1579***
	(0.0090)	(0.0093)	(0.0099)	(0.0102)
R^2	0.0120	0.0142	0.0158	0.0174
N	153,929	153,929	153,929	153,929
N. of tag-episode	93	93	93	93
TurnOnFeed	0.0132	0.0310**	0.0247**	0.0335**
	(0.0117)	(0.0150)	(0.0120)	(0.0141)
Diff: repBottom20 - repaboveBottom20	0.0480**	0.0374	0.0521	0.0434
	(0.0186)	(0.0275)	(0.0382)	(0.0384)
Mean	0.4147	0.4567	0.4868	0.5081

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

This table examines the robustness of the results in Table 9 to an alternative definition of low reputation, defining users with a reputation less than or equal to 20 as low reputation.

Heteroskedasticity robust standard errors clustered at the tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table A9. Low-reputation users benefit more from the chat rooms (controlling for low question quality)

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
TurnOnFeed*LowRep	0.0666***	0.0801***	0.0863***	0.0738**
	(0.0219)	(0.0263)	(0.0321)	(0.0310)
TurnOnFeed*HighRep	0.0104	0.0336**	0.0248**	0.0243
	(0.0128)	(0.0156)	(0.0120)	(0.0152)
HighRep	0.1325***	0.1452***	0.1540***	0.1613***
	(0.0092)	(0.0094)	(0.0099)	(0.0102)
TurnOnFeed*LowQuality	-0.0517*	-0.0693**	-0.0726**	-0.0257
	(0.0281)	(0.0266)	(0.0291)	(0.0274)
LowQuality	-0.0122**	-0.0142***	-0.0140***	-0.0151***
	(0.0053)	(0.0048)	(0.0048)	(0.0047)
R^2	0.0127	0.0148	0.0164	0.0180
N	153,929	153,929	153,929	153,929
N. of tag-episode	93	93	93	93
Diff (marginal): HighRep - LowRep	-0.0562***	-0.0466*	-0.0616	-0.0494
	(0.0195)	(0.0278)	(0.0381)	(0.0386)
Diff (total): HighRep - LowRep	0.0981***	0.0986***	0.0997***	0.1004***
	(0.0260)	(0.0259)	(0.0259)	(0.0260)
Mean	0.4147	0.4567	0.4868	0.5081

* p<0.1; ** p<0.05; *** p<0.01
Heteroskedasticity robust standard errors clustered atcthe tag-episode level in parentheses. Includes tag-episode level fixed effects, weekly dummies, and weekday dummies.

Table A10. Experience: Three-way interaction, compared to no PSM tags, linear combination

	AcceptHour (1)	Accept2Hour (2)	Accept4Hour (3)	Accept8Hour (4)
Panel A				
TurnOnFeed*LowQuality*LowRep	0.1106***	0.1076**	0.0806*	0.1134***
	(0.0335)	(0.0440)	(0.0484)	(0.0326)
TurnOnFeed*LowQuality*HighRep	-0.0724**	-0.0671*	-0.0695*	-0.0226
	(0.0291)	(0.0342)	(0.0359)	(0.0372)
TurnOnFeed*HighQuality*LowRep	0.0254	0.0385	0.0576*	0.0458
	(0.0220)	(0.0241)	(0.0328)	(0.0344)
TurnOnFeed*HighQuality*HighRep	0.0193	0.0426**	0.0309**	0.0302*
	(0.0137)	(0.0165)	(0.0122)	(0.0162)
Panel B				
QAsite*LowQuality*LowRep	-0.1597***	-0.1759***	-0.1850***	-0.1933***
	(0.0107)	(0.0113)	(0.0116)	(0.0120)
QAsite*LowQuality*HighRep	-0.0058	-0.0070	-0.0067	-0.0078
	(0.0050)	(0.0050)	(0.0050)	(0.0049)
QAsite*HighQuality*LowRep	-0.1243***	-0.1360***	-0.1447***	-0.1520***
	(0.0095)	(0.0098)	(0.0105)	(0.0110)
QAsite*HighQuality*HighRep	0	0	0	0
	(-)	(-)	(-)	(-)
Panel C				
LowQuality*LowRep	-0.0491	-0.0683	-0.1045**	-0.0800**
	(0.0325)	(0.0429)	(0.0474)	(0.0312)
LowQuality*HighRep	-0.0782***	-0.0741**	-0.0762**	-0.0304
	(0.0290)	(0.0342)	(0.0359)	(0.0374)
HighQuality*LowRep	-0.0988***	-0.0975***	-0.0871***	-0.1062***
	(0.0196)	(0.0219)	(0.0312)	(0.0326)
HighQuality*HighRep	0.0193	0.0426**	0.0309**	0.0302*
	(0.0137)	(0.0165)	(0.0122)	(0.0162)
Mean	0.4147	0.4567	0.4868	0.5081

* p<0.1; ** p<0.05; *** p<0.01
The table analyzes the effect of the feed on the likelihood of receiving an answer to questions with different combinations of reputation and quality. It is the analog to Table 12 in the text for durations other than 2 hours. Panel A shows the marginal effects of the feed and how it differs based on reputation and quality. Panel B shows the likelihood that a question will be answered based on quality and reputation if it is not treated by the feed. Panel C summarizes panels A and B by combining their effects to show the total relative magnitudes of the likelihood that a question will receive an answer within 2 hours when pushed into a chat room.

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