Behavior Toward Newcomers and Contributions to Online Communities

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ABSTRACT

In this paper, we study whether and how behavior toward newcomers impacts their socialization outcomes in terms of retention and quality of contributions in online communities. By exploiting a natural experiment on a large deal-sharing platform, we find that an intervention that proactively reminds other community members to be more considerate of newcomers causes newcomer deals to receive 54% more comments with a more positive sentiment. The newcomers are 10% more likely to post another deal, suggesting an increase in retention. However, we do not observe any effect of the intervention on the quality of subsequent contributions. Our evidence suggests that the intervention merely caused a temporary shock to newcomers' first contributions but did not improve their learning or motivate greater efforts. We draw implications on the design of socialization processes to help communities improve the retention and performance of newcomers.

Keywords: Online communities, newcomers, socialization, natural experiment
Supplementary Appendix: The supplementary appendix is available at https://osf.io/frceu/?view_only=1f5aaf67334c453491b0de93032a4ca4.

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INTRODUCTION

A central concern of online communities is motivating the sustained contribution of knowledge. Newcomers are an important source of knowledge contribution because they often have a different background, experience, and perspective when compared with existing members. Their knowledge can be of great marginal benefit to online communities (Ransbotham & Kane, 2011; Ren et al., 2016). However, newcomers may also ask questions and make comments that existing members have seen or answered before. They must "learn the ropes," ensuring that they make valuable contributions to integrate with existing members (Kraut et al., 2012). This process of transforming from being an outsider to an insider is called *newcomer socialization* (Louis, 1980). Insiders—existing members of the community—play a pivotal role in this socialization process (Joyce & Kraut, 2006). They shape newcomers' initial interaction experience with the group and directly affect whether newcomers feel liked and accepted by other community members. They also provide valuable guidance for newcomers to learn how to better function in the new environment.

Because existing members affect how newcomers adjust to the new environment, their behavior toward newcomers has important implications for communities to attract continuous contributions from new members. The prevailing focus of the literature on newcomer socialization has been on proactive strategies of newcomers to persuade existing members to support them, including membership claims and information seeking behaviors (e.g., Ahuja & Galvin, 2003; Burke et al., 2010), and interventions to educate and retain newcomers, including awards (Gallus, 2017), behavioral information (Chen et al., 2010), and collective socialization tactics (Tausczik et al., 2018). An important outstanding question is how online communities can shape the behavior of existing members to facilitate newcomer socialization.

This question is important because newcomers may differ in their propensity to participate positively and actively in the socialization process (Miller & Jablin, 1991). Thus, not all newcomers proactively accustom themselves with existing members. Even if a community can educate newcomers and prompt them to be proactive, they may not comply with the norms or policies hidden in the community. Accordingly, their contributions might face scrutiny, which could demotivate and drive valuable newcomers out of the community (Ren et al., 2016). In practice, online communities often have policies to encourage existing members to be friendly to newcomers. Examples include Mozilla's "Be Kind to Newcomers" and Wikipedia's "Don't Bite the Newcomer" policies. These policies may, however, not be faithfully read by all existing members. If an existing member posts a hostile message to newcomers, even if the community can remove the message afterwards, the newcomers may have decided to leave the community because the damage is already inflicted.

In this study, we advance a novel strategy to improve the behavior toward newcomers, viz. anticipatory excuses, where a contributor's newcomer status is nudged to other members *before* they engage with his/her post (Greenberg, 1996; Higgins & Snyder, 1989). This strategy is common in offline contexts: organizations use badges to identify new employees in situations where public scrutiny is expected. The idea is to discourage observers from attributing the newcomer's performance to internal factors (e.g., lack of ability) for which blame might be justified. Instead, we encourage attributing the performance to external factors (e.g., inexperience) for which the newcomer should be excused (Greenberg, 1996). In the context of online communities, we theorize that existing members may see inexperience as a plausible cause for poor contributions (Kelley, 1973). When an anticipatory excuse alerts existing members to a contributor's newness, the existing members may discount the role of ability in evaluating the newcomer's contribution.

We are particularly interested in whether anticipatory excuses through nudging existing members about a contributor's newcomer status can help improve the socialization outcomes in terms of retention and contribution quality. Do newcomers translate more positive responses from existing members into sustained, and more valuable, contributions? The reinforcement literature suggests that this is likely because positive responses may amplify intrinsic motivations—attention from others tends to make people feel good about themselves (Delin & Baumeister, 1994). However, positive outcomes may not occur if newcomers do not acquire relevant knowledge about their environment due to the lack of critical feedbacks (Wilhelm et al., 2019) or if they have a natural propensity to maintain their initial (low) levels of activities (Panciera et al., 2009).

Here, we use a *newcomer nudge* to study the effects of revealing a contributor's newness on (1) existing members' behavior toward newcomers and (2) newcomers' retention and future contribution quality.[1] Our empirical strategy is difference-in-differences (DID), exploiting a natural experiment on a deal-sharing community dedicated to price promotions. The community allows users to post deals and vouchers. Other members can rate the post quality by upvoting or downvoting them, or making comments. Since October 20, 2016, the community has displayed the nudge above the comment field of a newcomer's *first* post (Figure 1). The nudge is permanently attached to the post and visible even after the contributor has published additional posts. It affects only newcomer posts. To our knowledge, the nudge was not announced in advance and the community did not make any other major changes around the time when it was introduced.

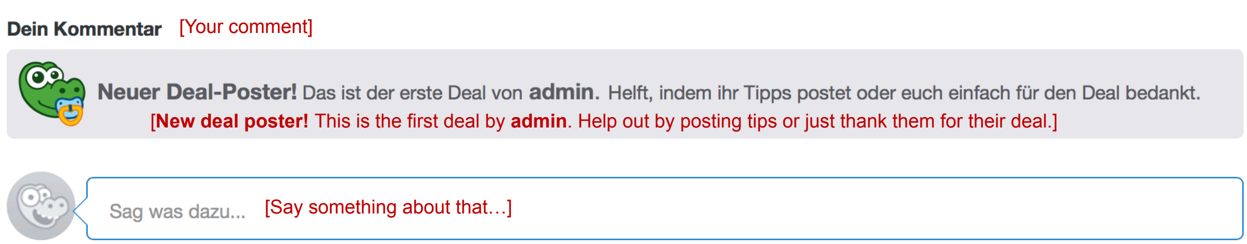

Figure 1: The Nudge

Our DID estimation shows that the nudge caused newcomer deals to receive 54% more comments with a more positive sentiment, indicating that anticipatory excuses indeed lead to more enthusiastic responses from existing members. We also find that newcomers socialized with the nudge were 10% more likely to post another deal within 12 months, but the quality of their subse-

[1]A nudge is any aspect of a choice architecture (e.g., user interface) that alters people's behavior in a predictable way without restricting the freedom of choice. For more discussion of nudges, see Thaler and Sunstein (2008).

quent contributions did not improve. Hence, the nudge facilitates newcomer retention, but it does not have a significant or sizable effect on their contribution quality.

This paper makes three contributions. First, it contributes to the literature on interventions to socialize newcomers in online communities. Many studies have documented positive outcomes of socialization programs, such as collective socialization (e.g., Li et al., 2020; Tausczik et al., 2018). However, the success of these programs often hinges on the extent to which newcomers show good citizenship behavior after being educated by them. We highlight a different but related approach—socialization outcomes are malleable to changes in insiders' behavior, too. This new focus (on insiders instead of newcomers) provides a powerful alternative for online communities to enhance the newcomer socialization process.

Second, this study is the first to examine how a positive distortion of existing members' behavior relates to different aspects of socialization, specifically, newcomer retention versus contribution quality. Prior work has shown that positive responses to newcomers can improve retention through a reinforcement mechanism (Joyce & Kraut, 2006; Phang et al., 2015). This paper shows that the benefits of positive reinforcement do not translate to enhancement of contribution quality. We advance the lack of change in task-relevant knowledge sharing as a plausible reason for why the newcomers do not improve. The implication is that the positive effects of institutional pressure toward lenient treatment of newcomers are contingent on having the right enabling environment—one that instills task-relevant knowledge in newcomers.

Third, this study contributes to a growing literature on using anticipatory excuses to preempt the negative effects of service failure, for example, by providing trainee badges to inexperienced employees (Flacandji et al., 2023; Greenberg, 1996). Prior research has established the value of signaling employees' inexperience to external customers. This study also shows its effectiveness in interaction with insiders. It suggests that communities can influence content production upstream—*before* the content is published—complementing research that has focused on moderating content downstream, i.e., *after* the content has been published (Jiang et al., 2023).

RELATED LITERATURE

We draw on the literature on newcomer socialization in online communities and anticipatory excuses to frame our contributions.

Newcomer Socialization in Online Communities

Socializing newcomers is central to online community success because newcomers can replace departing members and contribute new knowledge (Ren et al., 2012). Our work is particularly related to two streams of socialization research: (1) how interventions affect socialization outcomes and (2) the influence of insiders' behavior.

First, a growing body of research studies community interventions to socialize newcomers (Gallus, 2017; Li et al., 2020; Tausczik et al., 2018). These interventions primarily promote newcomers' effective functioning in the new environment to improve their retention and contribution quality. For example, in the WikiEd program, students make Wikipedia edits as a class assignment (Li et al., 2020). Newcomers who participated in the program were twice as likely to continue contributing, and made higher-quality edits. By contrast, an interactive game that helped newcomers accomplish tasks on Wikipedia had no discernible impact on their activities despite its popularity (Narayan et al., 2017). The literature has shown that the outcomes of socialization interventions are closely tied to newcomers' capabilities and citizenship behavior after getting onboard. We depart from this literature by examining whether socialization outcomes can be improved by interventions independent of newcomers' initial behavior. The advantage of our approach is that communities can provide a more positive and consistent new user experience even if newcomers are not acquainted yet. Such an approach has not been tested in the literature.

Second, prior research has examined the role of insiders in the socialization process. Insiders shape the environment in which newcomers try to fit in. Receiving a response to their posts can increase newcomers' likelihood to post again because it indicates that the community will be positive and receptive (Joyce & Kraut, 2006; Lampe & Johnston, 2005; Zhang et al., 2013). However, research has also suggested that newcomers who receive high-quality answers might reduce contributions in the belief that their own contributions are not needed (Yan & Jian, 2017). Aside from the inconclusive findings, these studies are observational, making it difficult to tease out the causal influence of insiders' responses on socialization outcomes.[2] In particular, people interested in the community might have a natural propensity to participate, causing their posts to receive more responses from existing members. To more precisely identify the causal influence of community response on newcomer behavior, it is essential to examine exogenous changes in insiders' behavior. The nudge in this study serves as one such exogenous change.

Anticipatory Excuses and Inexperience

This study is also related to research on anticipatory excuses (Higgins & Snyder, 1989)—the attempt to provide an excuse for a performance that has yet to be evaluated (Greenberg, 1996). Whereas retrospective excuses aim to distance the actor as much as possible from a particular performance *after* the act, anticipatory excuses are disseminated *before* the anticipated (poor) performance (Snyder & Higgins, 1988). The goal is to preemptively weaken the link between the actor and a subsequent outcome. Thus, anticipatory excuses are often used when the actors will predictably not meet the performance standard, for example, when they are inexperienced. Research has shown that revealing employee inexperience through a badge or corporate uniform can modify perceptions of service quality (Flacandji et al., 2023; Greenberg, 1996). Greenberg (1996)

[2] Several papers note this shortcoming. Joyce and Kraut (2006, p. 743) note that "[o]urs is not experimental research. Therefore, we cannot definitely say that the empirical relationships shown here [...] between getting a reply and posting again, are causal." Yan and Jian (2017, p. 16) note that "this study is not a controlled experiment. So none of the relationships we have identified is, strictly speaking, causal. However, we have taken measures to make sure our predictors (community response) preceded the outcomes (i.e., future participation)." Zhang et al. (2013, p. 1121) note that "[i]t is likely that some unobserved heterogeneity or omitted variables that influence a member's likelihood of receiving responses from the community also influence his continued participation in the community."

find that people who asked others to forgive them because they were new to their job were more likely to be excused for poor performance. Flacandji et al. (2023) find that customers who experienced a service failure were more likely to remain loyal to the organization after encountering an inexperienced employee than an experienced employee. In this case, the poor performance was attributed to the employee's inexperience instead of the organization.

The literature reviewed above pertains to encounters between new employees and external customers. In contrast, our study focuses on shifting the behavior of insiders, that is, existing members of a community. Insiders have a longer tenure and hence could be more protective of community quality than customers (Ren et al., 2023). Furthermore, absent traditional social signals, text-based asynchronous communications in online communities are less personal (Ma & Agarwal, 2007). Whether revealing the inexperience of a newcomer can defuse insiders' dissatisfaction with his/her contributions in an online context is unclear.

THEORY AND HYPOTHESES

We draw on the attribution theory (Kelley, 1973) to analyze how the nudge may shape the behavior of existing members toward newcomers. The attribution theory explains how people may attribute a cause to someone's behavior and the consequences of such attribution (Jones et al., 1987). It posits that the interpretation of others' behavior plays an important role in determining reactions to the behavior. In our setting, the nudge provides a cause (inexperience) for newcomers' performance. The expected consequence is that other members may respond more leniently by providing (1) more responses (2) with a more positive sentiment. Specifically, by introducing the nudge, the platform provides an excuse for newcomers by highlighting their inexperience *before* others respond to them. Similarly to a trainee badge (Greenberg, 1996), the nudge can therefore be considered an "anticipatory excuse" (Higgins & Snyder, 1989).

The effectiveness of the anticipatory excuse results from the predictions of the discounting principle (Kelley, 1973). By definition, newcomers have had less exposure to the community than existing members. Therefore, they have fewer opportunities to learn about the community's policies and norms. Poor performance may be expected when newcomers post for the first time, allowing existing members to discount the role of ability as the behavior-correspondent disposition. After seeing the nudge, we expect existing members to accept newcomers' inexperience as a legitimate explanation for poor performance, which they attribute to situational pressure and less to the inherent ability of the person. Hence, we expect existing members to become more responsive and forgiving when evaluating the contributions of newcomers. Furthermore, the augmentation effect in attribution suggests that if a person can rise above conditions (e.g., inexperience) that would lead them to perform poorly, good performance may be perceived as internally caused, leading to inflated perceptions of such good performance (Greenberg, 1996; Kelley, 1973). In other words, if newcomers perform unexpectedly well, their contributions may be seen as particularly positive.

Taken together, the analysis above points to a positive effect of the nudge on the behavior toward newcomers because: (1) existing members may discount the role of ability if newcomers perform poorly and (2) they may augment the role of ability if newcomers perform well. We expect the nudge to encourage existing members to leave more comments on newcomer contributions and these comments, on average, should be more positive. Therefore, we hypothesize that:

H1: *Newcomer contributions receive more comments after the nudge.*

H2: *The sentiment of comments posted on newcomer contributions is more positive after the nudge.*

The impact of the nudge on existing members' behavior toward newcomers captures only the initial socialization process. The final socialization outcomes depend on how often the acquainted newcomers post, and what do they post, after being socialized into the community. In the following, we therefore focus on the two primary socialization outcomes (e.g., Li et al., 2020)—retention and contribution quality—after the nudge intervention has shifted the existing members' responses.

Retention. Positive responses may increase newcomers' future contributions because people tend to repeat actions that lead to positive reinforcements (Joyce & Kraut, 2006). Contributors who perceive themselves to be well connected in the community are more likely to contribute because they receive acknowledgment from others (Phang et al., 2015). Research has offered several theoretical explanations for such reinforcement. One emerges from the finding that an individual's behavior depends on its consequences (Ferster & Skinner, 1957). For example, in a conversation, speakers are more likely to express their opinions when their conversation partners agree with them (Verplanck, 1955). Receiving more responses may also amplify intrinsic motivations because attention from others creates a positive mood and makes people feel good about themselves (Delin & Baumeister, 1994). If the nudge increases newcomers' exposure to positive responses, it may reinforce their decision to stay in the community. In contrast, negative social experience may lead to alienation. If insiders reject a newcomer, the newcomer may stop asking questions or leave the community for fear that they might be perceived as "bugging" (Miller & Jablin, 1991, p. 97).

Another explanation for the positive reinforcement is that individuals reciprocate others' support by paying it forward (Gouldner, 1960). Newcomers might feel indebted and obligated to reciprocate the beneficial resources that they have received from existing members (see Joyce & Kraut, 2006, who suggest reciprocity as a mechanism underlying newcomers' information-sharing behavior). Both the inclination to experience positive reinforcements and the perceived obligation to reciprocate others' responses support our conjecture that the change in behavior toward newcomers will result in a higher likelihood for their return. Therefore, we hypothesize that:

H3: *The retention of newcomers is higher after the nudge.*

Contribution Quality. Whether nudge-induced positive responses from existing members can lead to higher quality of future contributions is an open question. The literature on socialization has argued that "positive reinforcement induces more learning than negative reinforcement" (Cable

& Parsons, 2001, p. 7). Socializing with insiders may help newcomers internalize the community's values. Thus, if the nudge promotes positive interactions between newcomers and existing members, it may help newcomers improve the quality of their subsequent contributions, too.

However, individuals may also learn from negative feedback and use that knowledge to improve their contributions (Wilhelm et al., 2019). Negative feedback is particularly effective in arousing cognitive awareness that leads to adaptation and change, meaning lacking such feedback may lead to quality degradation. As illustrated by a Stack Overflow member, negative feedback can serve as a reminder for newcomers to include missing information: "Yes[,] it is hard for beginners. But I have to admit that the negative feedback helped me to write better questions. At start I was a bit lazy and did not provided [sic] enough details and people were downvoting me, but that's [...] how I learned to always provide enough details" (Black, 2019).

Lastly, barriers against joining a group and initiation rituals could increase newcomers' commitment and loyalty and motivate them to post high-quality contributions (Kraut et al., 2012). People like groups more when they have endured more rigorous initiation processes (Aronson & Mills, 1959), which allows them to reconcile their perception of themselves as intelligent people in light of the actions they have undertaken to become part of the group. Therefore, if the nudge softens the initiation process for newcomers by making existing members act more positively, newcomers might have a higher chance of staying in the communities but feeling less committed to making high-quality contributions in the future (see Kraut et al., 2012). Overall, the existing theories do not point to an unequivocal impact of the nudge on contribution quality. Therefore, we formulate the following competing hypotheses:

H4a: *The quality of newcomers' subsequent contributions is higher after the nudge.*

H4b: *The quality of newcomers' subsequent contributions is lower after the nudge.*

SETTING

The community of interest is mydealz, a large German consumer-to-consumer community dedicated to sharing, rating, and reviewing deals and vouchers. Similar communities exist in other countries, such as Slickdeals.net in the US or hotukdeals.com in the UK. Members post deals and vouchers that can be up- or downvoted by others. The net number of votes (upvotes minus downvotes) is called the deal temperature. If a deal receives a temperature above 100, it is "hot" and if it is downvoted to below zero, it is "cold" (Figure 2). Deals are displayed in reverse chronological order. Well-received deals are selected by editors to appear on a highlight page, i.e., the default landing page for visitors. In addition to voting, members can write comments below a deal.

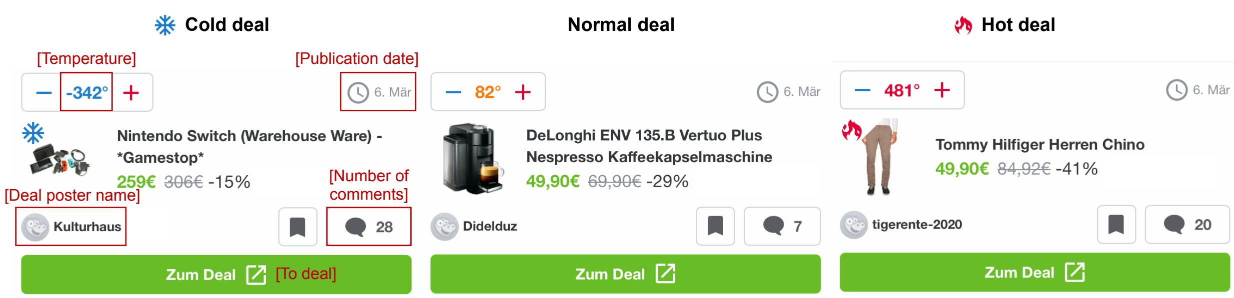

Figure 2: Examples of a Cold, Normal, and Hot Deal

We conducted semi-structured interviews with 18 users to assess the suitability of mydealz for studying behavior toward newcomers (Supplementary Appendix E). The interviewees observed negative comments directed at newcomers, such as when newcomers make mistakes:

> They're pretty quick to go after people who are beginners and don't know exactly, okay, what's a good deal now, how do I make the best price comparison, and so on. So, yes, [on these deals] hate comments are usually pouring in very fast.

The interviewees also shared that other members made fun of newcomer deals that did not offer much saving. Some interviewees believed that new contributors face a lot of scrutiny regarding their adherence to the community's policies (e.g., on mydealz, stated prices must always include shipping costs and contributors must conduct a thorough price comparison).

> I had the feeling that there's always a lot of criticism, that you can't make any mistakes, that you have to pay close attention to the wording and as soon as you somehow have something in there, that it's then immediately noted, criticized, you're [...] stoned.

Observations like these motivated mydealz to implement the nudge, which provides an excellent opportunity to study how online communities can better socialize newcomers as the negative behavior that had existed on mydealz has discouraged some users from ever posting again.

DATA

To analyze the effect of the nudge on newcomer deals and socialization outcomes, we collected historical data from mydealz. In our main analysis, we consider deals posted between July 22, 2016, and January 17, 2017, covering 90 days before and 90 days after the introduction of the nudge. In Supplementary Appendix A, we describe the data collection and preparation process. The deals cover a broad range of products in multiple categories such as electronics, food and drink, and household and garden. For each deal, we recorded the contributor's user name, publication date (*Day*) and hour (*Hour*), title, description, net number of votes (*DealTemp*), number of comments (*NumComments*), number of categories (*NumCategories*), content type (*Content*; 0=deal and 1=voucher), and whether it is restricted to a certain location (*LocalDeal*).

We count the description length in words (*DescLen*) and record the commenter's user name, day, and comment text to identify its length (*AvgCommentLen*) and sentiment. We measure the average sentiments of the comments using the German sentiment analysis tool provided by Microsoft's Azure Cognitive Services (API version *2021-04-30*). Azure Cognitive Services, such as its Face API, are well-established and used in prior research (Malik et al., 2023). Microsoft's sentiment analysis applies well to texts with more extreme opinions (Pallas et al., 2020), which is typical for online communities. It returns three non-negative sentiment scores for each comment—a positive score (*Positive*), neutral score (*Neutral*), and negative score (*Negative*). The three scores sum to 1. We also collected data from each contributor's public user profile, including the date they joined the community to compute their tenure in months (*Tenure*). Taken together, we constructed a cross-sectional data set with one row for each deal. Our data set includes all comments written up to the point of data collection. Table 1 presents summary statistics of our data. The deal temperature and description lengths differ markedly between newcomer and non-newcomer deals.

Table 1: Summary Statistics of Newcomer and Non-Newcomer Deals

		Newcomer Deals					Non-Newcomer Deals					
Variables	Unit	*N*	Mean	SD	Min	Max	*N*	Mean	SD	Min	Max	*t*-statistic
DealTemp	degrees	4,952	191.36	465.18	-935	17,746	35,971	290.38	439.32	-1,105	20,668	14.14***
NumComments		4,952	18.47	173.96	0	10,693	35,971	20.07	68.39	0	6,474	0.64
DescLen	words	4,952	86.02	88.25	0	1,819	35,971	116.74	153.14	0	5,560	20.60***
NumCategories		4,952	3.87	2.15	1	13	35,971	3.85	2.09	1	16	−0.67
LocalDeal	dummy	4,952	0.19	0.40	0	1	35,971	0.14	0.34	0	1	−10.01***
Content	dummy	4,952	0.07	0.26	0	1	35,971	0.07	0.25	0	1	−0.51
Tenure	months	4,952	11.80	17.93	0	108	35,971	33.80	24.58	0	112	76.99***
AvgCommentLen	words	4,666	19.24	12.06	1	178	34,641	19.64	14.10	1	741	2.05**
Positive	0∼1	4,666	0.29	0.17	0	1	34,641	0.29	0.16	0	1	1.84*
Negative	0∼1	4,666	0.29	0.16	0	1	34,641	0.28	0.14	0	1	−1.22
Neutral	0∼1	4,666	0.42	0.18	0	1	34,641	0.42	0.17	0	1	−0.68

Note: SD = standard deviation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Socialization Outcomes. We constructed several measures to evaluate the effect on socialization (see "Effect of the Nudge on Socialization Outcomes"). Our measure of newcomer retention, *DealPosted*, is a binary indicator of whether users had posted any deals within the 12 months after their first deal. Our measures of contribution quality are defined as follows. Δ*DealTemp* measures changes in the quality of contributions by subtracting the deal temperature of the first deal from the average temperature of all deals that were posted by the same user within the 12 months after the first deal. As alternative measures of quality, we measure the average deal temperature of subsequent deals, *AvgDealTemp*, the average likelihood of users mentioning a price comparison in the descriptions of subsequent deals, *AvgPriceComp*, and, if both the original price and discounted price are available, the average percentage discount, *AvgDiscount*.[3] We analyze contribution quality only for users who had posted at least one deal in the 12 months following the first deal.

We also measure two outcomes for exploratory purposes. *AvgDescLen* captures the average description length of the subsequent deals over the 12 months after a newcomer's first deal. It reflects users' effort to produce subsequent deals. *DaysSecDeal* measures the time gap (in days) from the first to the second deal. It reflects users' interest in posting another deal after their inaugural deals.

[3]We describe the keyword extraction process for *AvgPriceComp* and *AvgDiscount* in Supplementary Appendix B.

Lastly, in our analysis of socialization outcomes, we control for the badges earned by users (primarily by existing members), which generally reflect their activity levels. Specifically, *BadgeDeal* is a binary indicator that denotes whether a user had posted at least 10 deals; *BadgeComment* is a binary indicator that denotes whether a user had posted at least 100 comments; *BadgeVote* is a binary indicator that denotes whether a user had rated at least 200 deals.

EMPIRICAL ANALYSIS AND RESULTS

Effect of the Nudge on Newcomer Deals

Model-Free Evidence

Figure 3 visualizes the long-term effects of the nudge. The plot spans 1,110 days ($\sim$3 years) with observations recorded in 30-day intervals. Figure 3(a) shows the median deal temperatures, which differ substantially between the newcomer and non-newcomer deals before the nudge. The gap narrowed significantly after the nudge. In particular, the median temperature of newcomer deals increased from about 50 to 150. Figure 3(b) shows a similar pattern for number of comments.

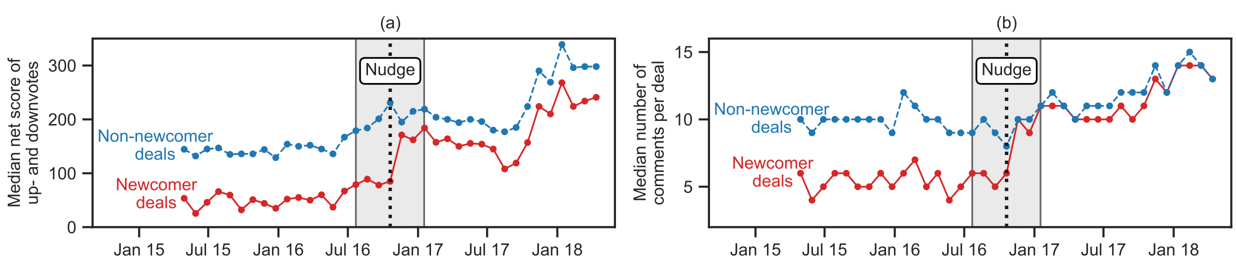

Figure 3: Newcomer vs. Non-Newcomer Deals in the Long Run (1,110 Days)

Note: The unit of observation is 30 days. The vertical dotted line indicates the introduction of the nudge. The shaded area between the two solid lines depicts the window of our main analysis (90 days pre- and post-nudge).

Regression Results

The model-free trends in Figure 3 do not account for control variables that might confound the nudge effect. To formally test H1 and H2, we use a DID strategy to identify the effect of the nudge on *NumComments* (H1) and the three sentiment scores, *Positive*, *Neutral*, and *Negative* (H2). Our unit of analysis is deal, with newcomer deals as the treatment group and non-newcomer deals as the control group. We consider the following ordinary least squares (OLS) regression, in which we vary the time windows between 3, 5, 30, and 90 days before and after the newcomer nudge:

$$y_i = \beta_0 + \beta_1 Newcomer_i + \beta_2 Newcomer_i \times After_i + \beta_3 Tenure_i + \gamma_1 X_i + \gamma_2 Day_i + \gamma_3 Hour_i + \varepsilon_i, \quad (1)$$

where y_i variously denotes the log-transformed number of comments (H1) and the sentiment scores of the comments on deal i (H2). *Newcomer* is a dummy variable that equals 1 if deal i is a newcomer deal and 0 otherwise. As the nudge does not affect deals posted before the policy change, *After* is set to 0 if deal i was posted before the introduction of the nudge and 1 otherwise. The coefficient, β_2, of the interaction term *Newcomer*×*After* represents the marginal effect of the nudge on the responses to newcomer deals posted after the policy change. The main effect of *After* was omitted because of collinearity with the day variables. *Tenure* denotes the number of months since the contributor of deal i joined the community (fixed at the day of the post).

The control variables, X_i, include deal characteristics, i.e., *LocalDeal*, *Content*, *DescLen*, and *NumCategories*. We include category dummy variables in X_i to account for differences between deal categories. In the sentiment score regressions, we control for the average length of comments, *AvgCommentLen* because comment length may affect content richness and hence the classification accuracy. *Day* and *Hour* are dummy variables to control for the published date and hour-of-day of deal i. As the deals usually receive most attention shortly after being posted, both *Day* and *Hour* may affect how others interact with the deals (e.g., deals published at night may attract fewer comments than deals published in the morning). Finally, ε_i captures the random error.

Table 2 shows the regression results with the standard errors, ε_i, clustered by user. Each column in Table 2 corresponds to one of the four time windows, 3 days, 5 days, 30 days, and 90 days before and after the nudge. The left-hand side of Panel A shows that *Newcomer* has a negative relationship with *NumberComments*, which indicates that newcomer deals generally received fewer comments than non-newcomer deals. Because the coefficients of the interaction term, *Newcomer*×*After*, are consistently positive and precisely estimated, H1 is supported. The coefficient obtained from the 90-day sample, for instance, is 0.435, indicating that the nudge led to a 54% increase in the number of comments during the first 90 days.[4] Among the control variables, *Tenure* and *DescLen* are positively correlated with *NumComments*, indicating that deals that convey more information and are posted by more experienced community members received more attention. Local deals attracted fewer comments than non-local deals, meaning they are of interest to fewer members. *Content* is negatively correlated with *NumComments*, meaning vouchers garnered less discussion than deals. The more categories a deal was assigned to, the more comments it has received.

Table 2 also shows the impact of the nudge on the sentiment scores. Comments on newcomer deals became significantly more positive after the nudge (except in the 3-day sample), but we do not observe a consistent and significant effect for negative or neutral sentiments. If anything, both sentiments seem to have decreased. These results indicate that the nudge improved the sentiment toward newcomer deals, which supports H2. We use the 90-day window as our preferred estimate.[5]

Validation

Parallel Trends. The identification of treatment effect in DID is based on the parallel trends assumption. In the absence of treatment, the treated and untreated (control) groups should follow a similar trend, i.e., their difference is relatively stable over time. We add a series of time dummies to capture the relative chronological distances between the observation time and the time when the nudge was introduced.

$$y_i = \beta_0 + \beta_1 Newcomer_i + \sum_{j=-6}^{5} \lambda_j Newcomer_i \times Distance_{ij} + \beta_3 Tenure_i + \gamma_1 X_i + \gamma_2 Day_i + \gamma_3 Hour_i + \varepsilon_i, \qquad (2)$$

where *Distance* is a dummy variable indicating the relative chronological distance j from the policy change using a 15-day time window. Equation (2) is similar to Equation (1), with *Newcomer*×*After* replaced by a set of dummy variables *Newcomer*×*Distance*. The coefficients λ_j help identify whether a pre-treatment trend existed and how the effect dynamically evolved after

[4] We calculate effect size as exp(0.435) - 1 = 54%.

[5] Our preference for the 90-day window is based on prior work (Foerderer et al., 2018) and the fact that the platform had implemented a new badge system three months before the nudge. Although the use of shorter windows produces significant estimates, the rapid decrease in sample size may affect the precision of the estimates.

Table 2: Test of H1 and H2: Effect of Nudge on Newcomer Deals

Panel A: Effect of Nudge on Number of Comments and Positive Sentiment

	log(1+*NumComments*)				*Positive*			
	±3 Days	±5 Days	±30 Days	±90 Days	±3 Days	±5 Days	±30 Days	±90 Days
Newcomer	−0.120	−0.192*	−0.269***	−0.362***	−0.027	−0.035**	−0.016**	−0.004
	(0.129)	(0.099)	(0.044)	(0.029)	(0.019)	(0.017)	(0.008)	(0.005)
Newcomer×After	0.322*	0.311**	0.393***	0.435***	0.038	0.065**	0.035***	0.012**
	(0.195)	(0.153)	(0.057)	(0.034)	(0.030)	(0.027)	(0.010)	(0.006)
Tenure	0.004***	0.005***	0.004***	0.003***	0.000	0.000	0.000	0.000**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
log(1+*DescLen*)	0.231***	0.208***	0.180***	0.159***	0.001	0.005	0.012***	0.011***
	(0.039)	(0.034)	(0.017)	(0.012)	(0.006)	(0.005)	(0.002)	(0.001)
LocalDeal	−0.389***	−0.300***	−0.371***	−0.372***	−0.008	−0.007	−0.018***	−0.018***
	(0.099)	(0.071)	(0.035)	(0.024)	(0.015)	(0.013)	(0.005)	(0.003)
NumCategories	0.077***	0.053***	0.044***	0.037***	0.001	−0.002	−0.002*	−0.002***
	(0.015)	(0.012)	(0.006)	(0.004)	(0.002)	(0.002)	(0.001)	(0.000)
Content	−0.596***	−0.552***	−0.518***	−0.545***	−0.041	−0.024	−0.012	0.002
	(0.144)	(0.098)	(0.047)	(0.024)	(0.027)	(0.021)	(0.008)	(0.004)
AvgCommentLen					0.002***	0.002***	0.001***	0.001***
					(0.000)	(0.000)	(0.000)	(0.000)
Time FE (Day, Hour)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,109	1,834	11,815	40,923	1,065	1,748	11,234	39,307
Adjusted R-squared	0.144	0.113	0.141	0.139	0.023	0.016	0.032	0.031

Panel B: Effect of Nudge on Neutral Sentiment and Negative Sentiment

	Neutral				*Negative*			
	±3 Days	±5 Days	±30 Days	±90 Days	±3 Days	±5 Days	±30 Days	±90 Days
Newcomer	0.013	0.022	0.007	−0.002	0.013	0.013	0.009	0.006
	(0.020)	(0.020)	(0.008)	(0.005)	(0.020)	(0.018)	(0.007)	(0.004)
Newcomer×After	−0.025	−0.049*	−0.021**	−0.006	−0.013	−0.016	−0.014	−0.007
	(0.029)	(0.027)	(0.011)	(0.006)	(0.026)	(0.023)	(0.009)	(0.005)
Tenure	0.000**	0.000	0.000	0.000	0.000	0.000	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(1+*DescLen*)	0.005	−0.002	−0.010***	−0.010***	−0.006	−0.003	−0.001	−0.001
	(0.006)	(0.005)	(0.003)	(0.001)	(0.006)	(0.004)	(0.002)	(0.001)
LocalDeal	0.038**	0.039***	0.041***	0.035***	−0.029**	−0.031***	−0.023***	−0.017***
	(0.017)	(0.013)	(0.006)	(0.003)	(0.015)	(0.011)	(0.005)	(0.002)
NumCategories	−0.001	−0.001	0.002**	0.002***	0.000	0.003	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.000)
Content	−0.033	−0.017	0.011	0.000	0.074***	0.041**	0.000	−0.001
	(0.031)	(0.021)	(0.008)	(0.004)	(0.028)	(0.019)	(0.007)	(0.004)
AvgCommentLen	−0.005***	−0.005***	−0.004***	−0.003***	0.003***	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Time FE (Day, Hour)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,065	1,748	11,234	39,307	1,065	1,748	11,234	39,307
Adjusted R-squared	0.137	0.123	0.109	0.106	0.082	0.074	0.066	0.067

Note: FE = fixed effects. Robust standard errors clustered by user are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

the new policy. We estimate Equation (2) with j ranging from -6 to 5, which evenly divides the 180 days of our main analysis into 12 periods. We set the first time period ($j=-6$) as the baseline by normalizing the coefficient of that time period to zero.

Table 3 presents the estimation results. None of the pre-treatment coefficients of *Newcomer*× *Distance* is statistically different from zero. By contrast, all post-treatment coefficients for *Num-*

Comments are statistically significant and positive. Three coefficients in the post-treatment periods of the sentiment regressions are marginally significant at $p < 0.1$ (*Positive* at $j = 0$, *Negative* at $j = 1$ and 2). These results suggest that changes in the number of comments and sentiment scores occur only after the policy change and that there are no spurious or erroneous associations.

Table 3: Dynamic Treatment Effect

	log(1+*NumComments*)		*Positive*		*Neutral*		*Negative*	
	(1)		(2)		(3)		(4)	
Newcomer	−0.337***	(0.067)	−0.004	(0.012)	−0.012	(0.012)	0.015	(0.011)
Newcomer×*Distance*$_{-5}$	−0.009	(0.095)	0.028	(0.017)	−0.007	(0.017)	−0.021	(0.015)
Newcomer×*Distance*$_{-4}$	−0.098	(0.094)	−0.004	(0.016)	0.020	(0.017)	−0.016	(0.015)
Newcomer×*Distance*$_{-3}$	−0.130	(0.093)	0.005	(0.016)	0.006	(0.016)	−0.012	(0.015)
Newcomer×*Distance*$_{-2}$	−0.033	(0.090)	−0.008	(0.016)	0.013	(0.017)	−0.005	(0.015)
Newcomer×*Distance*$_{-1}$	0.122	(0.093)	−0.017	(0.015)	0.023	(0.017)	−0.006	(0.015)
Newcomer×*Distance*$_{0}$	0.338***	(0.089)	0.025*	(0.015)	−0.012	(0.016)	−0.013	(0.014)
Newcomer×*Distance*$_{1}$	0.524***	(0.088)	0.021	(0.015)	0.004	(0.015)	−0.025*	(0.014)
Newcomer×*Distance*$_{2}$	0.361***	(0.079)	0.015	(0.014)	0.006	(0.014)	−0.021*	(0.012)
Newcomer×*Distance*$_{3}$	0.444***	(0.077)	0.011	(0.013)	0.008	(0.014)	−0.018	(0.012)
Newcomer×*Distance*$_{4}$	0.390***	(0.081)	−0.002	(0.014)	0.009	(0.014)	−0.007	(0.013)
Newcomer×*Distance*$_{5}$	0.416***	(0.080)	0.009	(0.014)	0.002	(0.014)	−0.012	(0.013)
Time FE (Day, Hour)	Yes		Yes		Yes		Yes	
Category FE	Yes		Yes		Yes		Yes	
Control Variables	Yes		Yes		Yes		Yes	
Observations	40,923		39,307		39,307		39,307	
Adjusted R-squared	0.139		0.032		0.106		0.067	

Note: FE = fixed effects. Robust standard errors clustered by user are in parentheses. Control variables include *Tenure*, log(1+*DescLen*), *LocalDeal*, *NumCategories*, and *Content*. Columns 2–4 additionally include *AvgCommentLen*. *** p <0.01, ** p <0.05, * p <0.10.

Spillover of the Policy Change. We need to rule out the possibility that the nudge could have affected non-newcomer deals, known as the stable unit treatment value assumption (SUTVA) (Eckles et al., 2017; Rosenbaum, 2007). We construct a proximity-based measure of exposure (Jo et al., 2020). We test whether the behavior toward non-newcomer deals depends on the number of treated deals posted before a non-newcomer deal. A potential spillover should be more pronounced for non-newcomer deals that directly compete for attention with the treated deals. We create the variable *NumTreatedDeals* that captures the number of newcomer deals published in the 30 minutes prior to a non-newcomer deal. We re-estimate Equation (1) by restricting to non-newcomer deals after the policy change. The results in Table 4 show that the coefficients of *NumTreatedDeals* are not statistically significant (odd columns). Thus, the nudge did not attract comments or lead to a sentiment change for non-newcomer deals.

Table 4: Testing for SUTVA and Compositional Changes

	log(1+*NumComments*)		*Positive*		*Neutral*		*Negative*	
	SUTVA (1)	Composition (2)	SUTVA (3)	Composition (4)	SUTVA (5)	Composition (6)	SUTVA (7)	Composition (8)
NumTreatedDeals	−0.003		0.000		0.001		−0.001	
	(0.006)		(0.001)		(0.001)		(0.001)	
SecondDeal		−0.194*		0.002		−0.010		0.008
		(0.103)		(0.018)		(0.019)		(0.014)
SecondDeal×*After*		0.168		−0.013		0.011		0.001
		(0.120)		(0.021)		(0.022)		(0.018)
Time FE (Day, Hour)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,467	35,966	19,785	34,636	19,785	34,636	19,785	34,636
Adjusted R-squared	0.131	0.130	0.033	0.030	0.094	0.103	0.067	0.070

Note: FE = fixed effects. Robust standard errors clustered by user are in parentheses. Control variables include *Tenure*, log(1+*DescLen*), *LocalDeal*, *NumCategories*, and *Content*. Columns 3–8 additionally include *AvgCommentLen*. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Compositional Changes. Given that our analysis uses a DID design with repeated cross sections (i.e., different deals posted before and after the nudge), it is important to address possible compositional changes (Athey & Imbens, 2006). First, compositional changes are less likely to occur in short time windows around the intervention because it is likely to take time for newcomers to become aware of the nudge. As shown in Table 2, the results of our analysis are consistent for short and long windows. Second, we compare the second deals of newcomers (which are not treated by the nudge) posted shortly after the first deal. If a compositional change has occurred, these deals may be different because they come from newcomers of different characteristics. We restrict our sample to deals posted within one week after the first deal. We choose the short, one-week window to ensure that the second deals are less influenced by newcomer learning. The variable *SecondDeal* equals 1 for a newcomer's second deal posted between 1 and 8 days of the first deal.[6] We remove observations with the second deals posted after the policy change but the first deals before. We also remove the first newcomer deals to prune the impact of the nudge in this analysis. The results in Table 4 indicate that the second deals do not receive more comments or have different sentiments after the change (even columns). This finding suggests that there is no evidence of compositional

[6]We exclude second deals posted within one day of the first deal because we find a number of duplicates or near duplicates among those deals (e.g., in-store promotion of the same local store). They often receive fewer comments or are marked as "expired" sooner. Including such entries might introduce noise to our estimation.

change, i.e., the newcomers before and after the policy change do not seem to differ.

Robustness Checks

Table 5 reports the robustness checks. In the odd columns, we show that our results are robust after removing deals posted by hyperactive members whose number of deals was more than three standard deviations (SD) above the mean (mean = 2.663, SD = 9.886). In the even columns, we include deals posted by deleted, banned, or employed members (Supplementary Appendix A). In Column (9), we use the percentage of negative words as an alternative operationalization of sentiment (Shen et al., 2015).[7] All of these estimations produce results consistent with H1 and H2, i.e., the nudge has aroused more responses and more positive sentiments on the newcomer deals.[8]

In Supplementary Appendix C, we show that the existing members changed their behavior because of the anticipatory excuse provided by the platform instead of the newcomer. We make this inference by leveraging the fact that some contributors revealed their newcomer status themselves and asked for forgiveness when posting the deals. We find that the nudge has stronger influences than self-disclosure, i.e., it has a robust positive effect on the number of comments and their sentiments even after controlling for the dissemination of the excuse through newcomers themselves.

Table 5: Robustness Checks

	log(1+*NumComments*)		*Positive*		*Neutral*		*Negative*		*PercNegWords*
	Outliers Removed (1)	All Users Included (2)	Outliers Removed (3)	All Users Included (4)	Outliers Removed (5)	All Users Included (6)	Outliers Removed (7)	All Users Included (8)	Main Model (9)
Newcomer	−0.376***	−0.438***	−0.001	−0.008*	−0.003	−0.002	0.004	0.009**	0.312***
	(0.027)	(0.033)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.088)
Newcomer×After	0.445***	0.441***	0.012**	0.013**	−0.006	−0.004	−0.006	−0.009*	−0.267**
	(0.032)	(0.033)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.106)
Time FE (Day, Hour)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,541	51,508	32,179	49,516	32,179	49,516	32,179	49,516	39,307
Adjusted R-squared	0.148	0.135	0.030	0.030	0.103	0.107	0.065	0.068	0.010

Note: FE = fixed effects. Robust standard errors clustered by user are reported in parentheses. Control variables include *Tenure*, log(1+*DescLen*), *LocalDeal*, *NumCategories*, and *Content*. Columns 3–8 additionally include *AvgCommentLen*. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

[7] We describe the derivation of percentage of negative words, *PercNegWords*, in Supplementary Appendix B.

[8] In Table B2 in Supplementary Appendix B, we show that the results are qualitatively unchanged when using a dictionary-based sentiment analysis on a subset of the comments translated to English.

Effect of the Nudge on Socialization Outcomes

To test H3 and H4a-H4b, we consider the effect of the nudge on newcomer retention and their contribution quality. We modify Equation (1) and drop the deal characteristics (X_i) and hour dummies of the first deal (*Hour*) because they are unlikely to account for differences in continuous user engagement. In addition to *Tenure*, which was used in Equation (1), we include a set of badges that users had earned before the focal deal to better capture users' motivation to contribute.

$$y_i = \beta_0 + \beta_1 Newcomer_i + \beta_2 Newcomer_i \times After_i + \beta_3 Tenure_i + \gamma_1 Badges_i + \gamma_2 Day_i + \varepsilon_i, \quad (3)$$

where y_i denotes retention or quality of contributions. In contrast to the main analysis, we modify the control group to capture changes at the user level. Specifically, because non-newcomers may have posted multiple deals in each period, we only selected each non-newcomer's first post in the pre-nudge and post-nudge periods. We consider these deals the "first deals" of non-newcomers and use their posting dates as the start of the 12-month time frame.

Retention

To test H3, we examine the effect of the nudge on retention, measured by a binary indicator, *DealPosted*, of whether a user posted another deal within the 12 months after the first deal. We estimate the effect of the policy change on this outcome using a linear probability model (LPM). The results are shown in Column (1) of Table 6. Because we find that newcomers in the post-nudge period are significantly more likely to post a deal in the 12 months after the first deal, H3 is supported. On average, the nudge increased newcomer retention by 3.7 percentage points (pp) compared to non-newcomers. Over the pre-nudge period, the probability of a newcomer to return within 12 months is 38%. We relate the DID coefficient to the baseline probability by dividing 0.037 by 0.38, which suggests a change of 9.7%. In Supplementary Appendix D, we repeat the same analysis for (1) the volume of deals and (2) comments. The results are consistent.[9]

[9] The results in Table 6 are robust to using a numerical variable, *NumPriorComments*, instead of *BadgeComment*. *NumPriorComments* denotes the number of comments posted by a user prior to posting deal i.

Table 6: Test of H3 and H4a-H4b: Effect of Nudge on Retention, Quality, and Motivation

	Retention	Quality				Motivation	
	DealPosted (1)	Δ*DealTemp* (2)	*AvgDealTemp* (3)	*AvgPriceComp* (4)	*AvgDiscount* (5)	*AvgDescLen* (6)	*DaysSecDeal* (7)
Newcomer	−0.230***	0.048	−0.557***	−0.005	−0.003	−0.077***	8.974**
	(0.013)	(0.200)	(0.125)	(0.016)	(0.011)	(0.028)	(3.810)
Newcomer×*After*	0.037**	−0.695***	0.185	−0.011	−0.011	−0.006	2.994
	(0.016)	(0.235)	(0.154)	(0.020)	(0.014)	(0.036)	(4.929)
Time FE (Day)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,153	11,757	11,757	11,757	5,205	11,757	11,757
Adjusted R-squared	0.114	0.017	0.033	0.003	0.014	0.034	0.044

Note: Δ*DealTemp*, *AvgDealTemp*, and *AvgDescLen* are log-transformed. Control variables include *Tenure*, *BadgeDeal*, *BadgeComment*, and *BadgeVote*. Robust standard errors clustered by user are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Quality of Contributions

To test the competing H4a and H4b, we analyze how the quality of the subsequent contributions of newcomers changed compared to their first contribution. We consider the change in quality, Δ*DealTemp*, using the sample of newcomers who posted another deal within 12 months after the first deal. We observe a statistically significant effect for Δ*DealTemp* (1.152 vs. 0.049, $t(2{,}024) = 5.238$, $p < 0.001$). Before the nudge, newcomers' subsequent deals received, on average, more upvotes than the first deal, indicating that newcomers improved over time. Surprisingly, after the intervention, Δ*DealTemp* is almost zero and much lower than the pre-nudge period. We formally conduct the analysis including non-newcomers who posted another deal within 12 months as a control group in estimating Equation (3). The results in Column (2) of Table 6 show that, indeed, the newcomers' second deal had lower temperature than their first deal relative to non-newcomers after the nudge. What causes such a relative drop in quality of the subsequent deal?

One explanation for the decline in Δ*DealTemp* is that in the absence of the nudge, existing members are less likely to discount the role of ability. Hence, they are more critical of newcomers' first deals, leading to the lower temperature of such deals and hence the larger Δ*DealTemp* before the nudge. This effect, due to anticipatory excuses of newcomers' first deals, would be absent starting from the second deal onwards. Accordingly, we expect the temperature of deals posted after the first deal, *AvgDealTemp*, to be similar before and after the nudge. Column (3) of Table 6 shows that, indeed, *AvgDealTemp* remains unchanged. Furthermore, Columns (4) and (5) show no significant differences using alternative measures of deal quality, i.e., the likelihood of users mentioning a price comparison in their deal description, *AvgPriceComp*, and the average percentage discount, *AvgDiscount*. Collectively, these results do not support H4a or H4b. Instead, the net quality of subsequent deals by newcomers is similar before and after the nudge, supporting the explanation that the change in Δ*DealTemp* may be attributed to the absence of the nudge on subsequent deals. In Supplementary Appendix E, we offer qualitative evidence in support of this explanation.

We now explore other explanations for why newcomers cannot surpass the quality of their first deals. The lenient feedback induced by the nudge may suppress the motivation of newcomers to learn—they do not have to work hard to get accepted into the group, so they spend less effort on subsequent deals. To identify a reduction in the motivation of newcomers after the nudge, we compare the average deal description length of the subsequent deals, *AvgDescLen*, and the time gap between the first and second deal, *DaysSecDeal*. The former reflects the effort put into subsequent deals. The latter indicates newcomers' general level of motivation to contribute. Columns (6) and (7) of Table 6 show no significant coefficients for the DID estimators of *AvgDescLen* and *DaysSecDeal*, suggesting that their effort and motivation had not changed.

The lenient behavior toward newcomers might reduce the information quality of the comments. Newcomers might then learn less and have a lower chance of translating their experience into more successful posts in the future. We use several machine learning classifiers to analyze how the helpfulness, usefulness, and informativeness of the comments change after the nudge (Supplementary Appendix F). The results suggest that the nudge has not reduced the percentage of helpful, useful, or informative comments on newcomer deals. Furthermore, we test whether newcomers in greater need of learning, e.g., those with a short tenure or few prior comments at the time of their first post, experience a more pronounced decline in Δ*DealTemp* between their first and subsequent deals. We find that the decline exists for both experienced and inexperienced newcomers (Table 7). These results suggest that learning suppression is unlikely to explain our findings.

Table 7: Change in Deal Temperature by Newcomer Experience

	(1) Low Experience Newcomers			(2) High Experience Newcomers		
Measure	Pre	Post	t-statistic	Pre	Post	t-statistic
Cumulative Comments						
Δ*DealTemp* (log)	1.251	−0.052	−3.702***	1.08	0.121	−3.704***
Observations	315	531		431	747	
Tenure						
Δ*DealTemp* (log)	1.045	0.007	−3.317***	1.248	0.093	−4.073***
Observations	352	651		394	627	

Note: The sample was split by the median into low and high experience newcomers. *** $p < 0.01$.

IMPLICATIONS AND CONCLUSIONS

Online communities face high turnover, particularly among newcomers. This paper is one of the first empirical studies on how an exogenous shock in existing members' behavior affects newcomer socialization outcomes in a deal-sharing community. By exploiting a natural experiment, we show that an intervention that proactively reminds people to be more considerate of newcomers causes newcomer deals to receive more comments (H1) with a more positive sentiment (H2). Consistent with H3, we find that newcomers are more likely to post another deal after the nudge, suggesting improved newcomer retention. However, the nudge has not affected the quality of newcomers' subsequent contributions, indicating that neither H4a nor H4b is supported.

Community Response and Socialization Outcomes

The positive impact of the intervention on retention suggests that interacting with other members positively reinforces continued participation. We find that newcomers in the post-nudge period are 10% (4 pp) more likely to post a deal in the 12 months following their first deal. How does this effect compare with other interventions? Two recent interventions on Wikipedia serve as good references. Gallus (2017) find an increase in retention by 13% (4 pp) in the month after newcomers receive a symbolic award. Li et al. (2020) find that newcomers who edited Wikipedia as part of the WikiEd program had a 51.2% reduction in the risk of dropping out one year after the end of the course than editors in the matched control group. However, the difference was only 2.1 pp due to the low probability that users were still editing after one year (2.1% in the control group, 4.2% in the treatment group). Evidently, the contexts and time windows are different between these studies and ours. However, these interventions, aiming at newcomers, appear to have a similar marginal effect on newcomers' probability to stay active as our study, which aims at existing members. We believe encouraging existing members to be more friendly is a promising low-cost alternative strategy to retain newcomers in the community.

We also compare our effect size with an observational study that examined the role of insiders in the socialization process. Joyce and Kraut (2006) find that newcomers who received a response were 12 pp more likely to post to the community again. The coefficient is about three times larger than our estimate obtained from an exogenous shock (0.124 compared with 0.037).[10] This discrepancy could arise from endogenous responses, that some newcomers have a stronger propensity and are better accustomed to stay in the community, and they tend to interact more with insiders. Our setting of an exogenous natural experiment better controls for such endogenous responses.

Our finding informs the broader tension of whether active and committed community members are born or made, particularly, through their interaction with existing members (e.g., Panciera et al., 2009). We contribute new empirical evidence that feeling socially accepted by insiders makes newcomers more likely to return independently of their intrinsic propensity to participate. However, this effect is likely to be smaller than that reported in observational studies.

Despite better retention, the initial interaction need not affect the quality of subsequent contributions. Studies have suggested that newcomers learn through positive reinforcement (Cable & Parsons, 2001) and negative experience (Wilhelm et al., 2019). Our results show that the positive

[10] Joyce and Kraut (2006, p. 737) state that the coefficient 0.124 corresponds to an increase of 12.4%. The coefficient they obtain using the *dprobit* function in Stata is commonly interpreted as 12.4 pp because it represents the marginal effect on the probability of posting again. They mention that "39% of those who failed to receive a reply posted again over the next three months." Thus, we interpret that the increase is 12.4 pp or 32% (0.124 divided by 0.39).

reinforcement has not enhanced the quality of the newcomers' subsequent contributions. Further analysis in Supplementary Appendix F shows that, although existing members became nicer after the nudge, they did not provide more task-relevant knowledge in their comments. We cannot ascertain if this lack of task-relevant knowledge is the primary cause for the non-improving quality, but it seems to be a tenable explanation as receiving nicer comments means the newcomers may not have motivation to learn beyond the comments. We suggest future research to explore whether task-relevant knowledge can help enhance the long-term contribution quality of newcomers.

If, indeed, task-relevant knowledge can help newcomers enhance their learning and quality, then platform owners should consider how to design interventions to feed such knowledge to newcomers. For example, they can combine a nudge with formal socialization tactics, such as collective socialization (Li et al., 2020). On the other hand, if positive reinforcement helps newcomers enhance their contribution but the lack of subsequent quality enhancement is due to limited exposure to the treatment, then platform owners may consider extending the intervention to newcomers' contributions posted within a certain period of time instead of restricting it only to the first post. This would strengthen the positive reinforcement and hence the chance of making a lasting impact and create a more conducive environment for newcomers to learn and improve their contributions.

Revealing Newcomers in Online Communities

Attribution theory and research on anticipatory excuses suggest that the nudge may encourage insiders to discount the role of ability if they learn about the newcomers' status in online social interactions. Prior research on anticipatory excuses has tested their effectiveness in offline social interactions, for example, using badges or corporate uniforms (Flacandji et al., 2023; Greenberg, 1996). We show that revealing the newcomer status through a nudge in online communities, where interactions are arguably less personal, may serve as a powerful signal for existing members to treat inexperienced individuals more kindly. Interestingly, we find that this effect is stronger if the platform flags the newcomers than if the newcomers flag themselves. Prior research has not documented any difference between newcomer revelations through self-identification (e.g., in a conversation) or through a standardized badge provided by the organization (e.g., Flacandji et al., 2023). We suspect that this finding is unique to online interactions because observers might find it difficult to judge the credibility of information shared by contributors when they lack reliable social cues (e.g., body language) to verify the contributors' claims (Ma & Agarwal, 2007). This distinction has important theoretical implications; it suggests that relying on insiders' intrinsic interest to groom newcomers may not be as effective in online communities. To better model the newcomer socialization process, we need to establish the theoretical merits of parental measures, such as a nudge, with instructional nature as part of the socialization strategy of a digital platform.

Practically, the effectiveness of the nudge suggests that a simple behavioral intervention can produce significant impacts on the receiving parties (e.g., Gallus, 2017). By influencing the tone of user-generated content, the nudge can complement downstream content moderation initiatives (e.g., Jiang et al., 2023)—if the content submitted to the community is less toxic toward newcomers, platforms would conserve more resources to filter other problematic comments. The nudge may be especially useful when organizational or community practices or norms are buried in a large repository of information, or when tacit knowledge is commonplace in the community. This may be particularly the case for online social networks that focus on knowledge exchange and dissemination. For example, Stack Overflow has introduced a policy similar to the nudge that flags contributions from new users, arguing that "[t]here are just *too many* nuances to how the system works [...]; we need a safety net" (Post, 2018).

Generalizability to Other Communities

We conclude this paper by discussing the generalizability of its findings to other communities. Although we offer evidence from a deal-sharing community, we believe our findings are applicable to communities where people join for information exchange (see Ridings & Gefen, 2004) and where contributors must follow specific policies to participate (Kraut et al., 2012). For example, when asking a debugging question on Stack Overflow, users should include a minimal workable example so that other users can reproduce the problem. In such an environment, the nudge will likely be effective because it pushes other members to correct errors or answer questions that they would otherwise have ignored. By contrast, our findings may not generalize to communities where people join for social support or friendship, such as health support groups or online friendship networks. If people join a community to network with others who face similar situations and get emotional support, the community may already be a place where members are inclined to show pro-social behaviors regardless of whether the platform tells them to be nice. In such cases, an intervention that provides protection may neither be a necessary nor an effective mechanism to retain new users. Overall, we encourage future research to replicate this study in different contexts to scrutinize the boundaries of our findings.

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