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 online communities, such as retention and quality of contributions. Intuitively, more positive interactions should help newcomers adjust to the new environment, but the effect could be driven by endogenous responses: people interested in the community have an intrinsic propensity to participate, while their posts receive more positive responses from existing members. By exploiting a natural experiment on a large deal-sharing platform, we find that an intervention that reminds people to be more considerate to newcomers causes newcomer deals to receive 54% more comments with a more positive sentiment. In turn, we find that newcomers are 4% more likely to post another deal, suggesting an increase in retention. However, we do not observe any effect on the quality of subsequent contributions. Our evidence suggests that the intervention merely caused a temporary shock to the first contributions of newcomers, but failed to improve learning or motivate greater effort. We draw implications for 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 different backgrounds, experiences, and perspectives relative to existing members, and thus 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 (Ren et al., 2007). They must "learn the ropes," ensuring that they make valuable contributions to integrate with existing members. This process of transforming from being an outsider to an insider is called *newcomer socialization* (Louis, 1980). Insiders—existing members of the community—play an important role in this socialization process (Bauer et al., 2007; Ellis et al., 2017). They shape newcomers' initial interaction with the group and whether newcomers would feel liked and accepted by other community members. They also provide valuable information for newcomers to learn how to better function in the new environment. Hence, existing members' actions affect how newcomers adjust to the new environment.

In conventional organizations, the socialization process marks the beginning of a collaborative relationship between workers that can last for years. Classical theories of newcomer socialization suggest that insider support of newcomers should be positive, systematic, and standardized (Jones, 1986; Van Maanen & Schein, 1977). However, an important difference between online communities and conventional organizations is that members in online communities contribute voluntarily instead of being governed by an employment contract. Accordingly, turnover in online communities tends to be high, as most people never post again after their initial contributions (Joyce & Kraut, 2006; Ren et al., 2012). The uncertainty in newcomers' future participation, coupled with the use of asynchronous text-based communications, makes unconditional support of newcomers by existing members challenging (Tausczik et al., 2018). Existing members may use their discretion in deciding whether and how to provide support and information to newcomers. This raises two important questions: can online communities influence existing members' behavior toward newcomers? How does existing members' behavior toward newcomers influence newcomers' socialization outcomes, such as retention and the quality of future contributions?

It is challenging to examine the relationship between community response to newcomers and the newcomer socialization outcomes. The observed outcomes could be driven by endogenous responses: people interested in the community may have an intrinsic propensity to contribute. Because of their enthusiasm, their posts may receive more positive responses from existing members. Their socialization outcomes may reflect such intrinsic propensity instead of the treatment received from existing members. To more precisely identify the causal effect of existing members' behavior on newcomer socialization, we need an exogenous treatment.

Here, we examine a novel intervention: a *newcomer nudge* that prompts community members to be lenient to newcomers' posts.[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 quality of the posts by upvoting, downvoting, or making comments. Since October 20, 2016, the community has displayed a nudge as shown in Figure 1 above the comment field of a newcomer's *first* post. This nudge is permanently attached to the post; it is visible even after the poster had published additional deals, and it affected only newcomer posts. To our knowledge, the community did not make any other major changes around the time when the nudge was introduced, and the nudge was not announced to the community in advance. This exogenous treatment provides us with a unique

[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).

opportunity to study the effects of the nudge on (1) existing members' behavior toward newcomers and (2) newcomers' retention and future contribution quality.

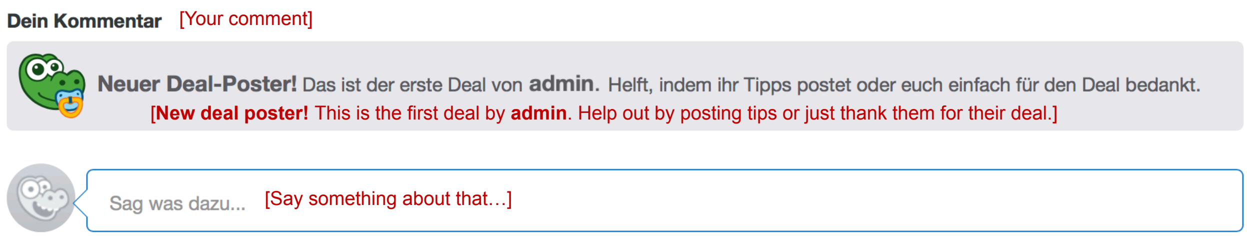

Figure 1: The Nudge

Our DID estimation shows that the nudge caused newcomer deals to receive 54% more comments with a more positive sentiment, indicating their improved acceptance by existing members. We also find that the newcomers socialized with the nudge were 4% more likely to post another deal within 12 months, but the quality of their subsequent contributions did not improve.

This paper makes three contributions. First, it extends research on the factors that impact how insiders socialize newcomers online (e.g., Joyce & Kraut, 2006) and offline (e.g., Dufour et al., 2021). Our finding that a simple nudge can substantially improve behavior toward newcomers is important for contexts where the potential contribution of newcomers is in doubt (e.g., temporary staff in organizations, first-time contributors in online communities). In these contexts, insiders are often reluctant to support newcomers. It might help to request existing members to be nice if the goal is to protect newcomers from initial intimidation.

Second, we pin down improved newcomer retention as an important socialization outcome due to a nudge-induced change in existing members' behavior. The literature, mostly based on observational data, is not conclusive on whether community response increases (C. Zhang et al., 2013), decreases (Yan & Jian, 2017), or has little effect on users' contributions (Rajadesingan et al., 2020). We contribute to this literature by establishing a causal link between newcomers' interactions and retention, indicating that positive socialization outcomes are not merely driven by the intrinsic interest of newcomers in the community, but also by the responses toward them.

Third, we extend the literature on interventions to socialize newcomers. Recent research has found evidence for a positive effect of organizational tactics, such as collective socialization, on the quality of edits by newcomers on Wikipedia (Li et al., 2020). We find that although positive responses can help retain newcomers, they may not improve newcomer quality. Instead, we find suggestive evidence that the positive responses due to the nudge led to initial achievements that were biased upward. The newcomers could not maintain the initial success without the nudge. Understanding the nuanced effects of the nudge offers useful design implications for online communities to on-board, retain, and improve the performance of newcomers.

RELATED LITERATURE

Extensive research has examined why people contribute to online communities (Ransbotham & Kane, 2011; Ren et al., 2012; Wasko & Faraj, 2005). Our review focuses on studies about newcomer contributions. Newcomer relationships with online communities are fragile and malleable (Chen et al., 2010), and often depend on how they are received by community members who shape their attachment to the community (Ren et al., 2007). Existing community members may attribute traits based on membership duration (*"newcomers are less experienced than old-timers"*) (Ren et al., 2016). Indeed, newcomer contributions may be under scrutiny by existing members as the following editor comment on Wikipedia well illustrates: "You're obviously new here, [...] arguing based on [the editing guidelines] is a bit ridiculous, like a kid just out of high school" (Kriplean et al., 2007, p. 173).[2] Not surprisingly, online communities struggle to retain newcomers. Socializing newcomers has become a major challenge to community success (Ren et al., 2012). Previous work has investigated various interventions and design considerations to promote newcomer contributions, including awards (Gallus, 2017), behavioral information (Chen et al., 2010), community characteristics (Ren et al., 2012), and monetary incentives (X. Zhang et al., 2017). We study a new

[2] We follow Ren et al. (2016) in using this quote.

tactic—promoting lenient behavior toward newcomers from other members via a nudge.

In the following, we review the organizational literature on the role of insiders in the socialization process, followed by a review of research on newcomer socialization in online communities.

The Role of Insiders in the Socialization Process

This study is related to a stream of research on the role of insiders (e.g., supervisors and peers) in the socialization process. In general, the literature suggests that insiders have a strong influence on the adjustment of newcomers to their new environment (Bauer et al., 2007; Kammeyer-Mueller et al., 2013). Insiders represent the environment into which newcomers try to fit in. Thus, newcomers may pay close attention to signals of social support, which indicate the environment will be positive and accepting, or destructive behaviors, which indicate the environment will be negative and rejecting. Kammeyer-Mueller et al. (2013) find that first impressions of newcomers determine their subsequent behaviors such as voluntary turnover. Shaping newcomers' initial interactions with insiders might serve as a lever for their successful adjustment.

Theories on newcomer socialization (Jones, 1986; Van Maanen & Schein, 1977) largely assume that insiders—especially supervisors—tend to support newcomers because it paves the way for a stable vertical career (see Dufour et al., 2021). However, the situation faced by newcomers in online communities is fundamentally different because they do not have a tangible commitment to stay on the platform.[3] This makes educating newcomers risky for existing members as their investments may not pay off. Dufour et al. (2021) study the socialization of newcomers who join firms through a temporary contract. They show that insiders are "autonomous decision-making and action-taking agents" who decide on the basis of initial evaluations of how to treat newcomers (Dufour et al., 2021, p. 882). Their findings pertain to how evaluations of specific newcomer

[3] Ren et al. (2012) report that in MovieLens.org, a popular community for movie ratings, the half-life of a new member was only 18 days.

behaviors (e.g., the ability to propose new feasible ideas) trigger supervisor responses (e.g., support for newcomer creativity) which, in turn, relate to outcomes (e.g., task performance).

Instead of studying the link between newcomer behavior, insiders' responses, and socialization outcomes (e.g., Dufour et al., 2021; Ellis et al., 2017), we highlight how an organizational intervention, viz. the nudge, impacts the way insiders socialize newcomers.

Newcomer Socialization in Online Communities

We now turn to research on newcomer socialization in online communities, especially works focusing on how responses by existing members shape socialization outcomes. Joyce and Kraut (2006) and C. Zhang et al. (2013) show that members who receive a response to their posts are more likely to post again. However, the characteristics of the reply, such as tone or length, did not influence the probability of future posting (Joyce & Kraut, 2006). By contrast, Yan and Jian (2017) find that newcomers who receive high-quality answers to their initial questions on Stack Overflow reduce their subsequent contributions because it may signal that their own contribution is not needed. Collectively, these studies form a good understanding of how newcomers' initial interactions with an online community may increase or decrease their commitments to the community. However, given the observational nature of these studies, newcomers who benefit from the interactions may already be committed to the group prior to their first posts. Such endogeneity could bias the inference of newcomer socialization through insiders.

Indeed, newcomers' commitment to the community is an important driver of retention. Lampe and Johnston (2005) show that the tenure prior to the first post and the number of page views requested were better predictors of the likelihood of posting a second comment than whether the first comment received a reply. Likewise, Rajadesingan et al. (2020) find that newcomers adjust their behavior before making their first posts to align with the typical behaviors exhibited by others. To causally identify how the behavior of newcomers is shaped by interactions with other community members, prior work suggests that an experiment is needed, where newcomers "receive controlled amounts of feedback and measure how their future participation differs" (Lampe & Johnston, 2005, p. 19). But conducting such an experiment in the field is difficult because manipulating or changing the behavior of existing members risks alienating valuable contributors.[4]

We also build on a growing body of research in human-computer interaction (HCI) that uses field experiments to study whether and which socialization tactics can help educate and retain newcomers in the context of Wikipedia (Li et al., 2020; Morgan & Halfaker, 2018; Tausczik et al., 2018). The interventions studied in these papers broadly follow the dimensions of classical socialization tactics identified by Van Maanen and Schein (1977). For example, Li et al. (2020) study the Wiki Ed program through which students make edits on Wikipedia as a class assignment. The program offers the options of collective socialization (students join as a cohort) and sequential socialization (assignments follow a meaningful sequence of steps). They find that, compared to a control group, the program was associated with larger improvements in the quality of articles on which the editors have worked. Tausczik et al. (2018) find that collective socialization serves as a buffer against negative feedback, in that editors improved the quality of their edits less in response to such feedback. These experiments provide causal evidence of selected tactics that make the new user experience less challenging, but focus on newcomers' behaviors rather than trying to change the "environment", viz. the existing members. As such, they treat existing members' responses, such as negative feedback, as exogenous inputs that newcomers either succeed, or fail, to navigate.

To our knowledge, this study is the first to investigate an intervention that encourages other members to be considerate of newcomers (cf. influencing newcomers themselves). We extend the literature by scrutinizing the causal link between community responses and socialization outcomes.

[4]In June 2023, Stack Overflow moderators and users went on strike to protest against changes to the platform that they feared would affect its quality. See https://meta.stackexchange.com/questions/389811/moderation-strike-stack-overflow-inc-cannot-consistently-ignore-mistreat-an.

THEORETICAL BACKGROUND

A positive response could increase the future contributions of newcomers because people tend to repeat actions that lead to positive reinforcements (Joyce & Kraut, 2006). For example, 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). Past research has offered several theoretical mechanisms to explain the 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 a response may also amplify intrinsic motivation 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 as an active member of the community.

In addition to motivation, the literature on socialization has also argued that "positive reinforcement induces more learning than negative reinforcement" (Cable & Parsons, 2001, p. 7). Socializing with organizational insiders may help internalize the community's values. Thus, if the nudge promotes positive interactions between newcomers and existing members in an online community, it may help newcomers improve the quality of their subsequent contributions. In contrast, negative social experiences may lead to alienation. If organizational insiders reject a newcomer, the newcomer may stop asking questions or leave the community out of fear that they might be perceived as "bugging" (Kammeyer-Mueller et al., 2013).

On the other hand, individuals may also learn about what does not work from negative feedback and use that information 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).

Another explanation for why the nudge can foster retention is that individuals reciprocate others' support by paying it forward (Gouldner, 1960). Newcomers might feel indebted and obligated to reciprocate for the beneficial resources that they receive from existing members due to the nudge (see Joyce & Kraut, 2006, who suggest reciprocity as a mechanism underlying newcomers' information-sharing behavior). Yet, newcomers sometimes perceive their own contribution as unnecessary, for example, if they expect others to provide sufficient contributions (Yan & Jian, 2017). Thus, in some cases, reciprocity may not improve knowledge-sharing behavior (see also Wasko & Faraj, 2005). Lastly, barriers and initiation rituals that cause newcomers to suffer before joining a group could increase their eventual commitment and loyalty (Honeycutt, 2005; Kraut et al., 2012). People like groups more when they have endured more rigorous initiation processes than those who have undergone milder initiations (Aronson & Mills, 1959). It 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 causes newcomers to undergo a milder initiation process, they might be more likely to stay in online communities but feel less committed and motivated to make high-quality contributions in the future (see Kraut et al., 2012). On balance, whether nudge-induced positive responses from existing members can lead to better retention and higher quality of future contributions is an empirical question.

SETTING

The community of interest is mydealz, a large German consumer-to-consumer community dedicated to sharing, rating, and reviewing deals and vouchers.[5] Members post deals and vouchers that are up- and downvoted by other members. 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 below zero, they are "cold" (Figure 2). Deals are displayed in reverse chronological order. Well-received deals are selected by editors to appear on a highlight page—the default landing page for visitors. In addition to voting, members write comments below a deal to discuss the product or improve the deal. We conducted semi-structured interviews with 18 users to appraise mydealz as an empirical context and assess its suitability to study behavior toward newcomers (see Supplementary Appendix E). The interviewees frequently observed negative comments directed at newcomers, such as when a deal poster makes a mistake, even if unintentional:

> 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 mentioned that other members made fun of newcomer deals that did not offer much saving potential. Some interviewees believed that new contributors faced a lot of scrutiny regarding their adherence to the community's guidelines (e.g., on mydealz, stated prices must always include shipping costs and posters must conduct a thorough price comparison. Voucher codes applicable only to new customers might be downvoted).

> 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.

These observations motivate why mydealz implemented the nudge. They also support using mydealz as the context to study how online communities can better socialize newcomers, as the negative behavior that had existed on the platform has discouraged some users from posting again.

[5] Similar communities exist in other countries, such as Slickdeals.net in the US or hotukdeals.com in the UK.

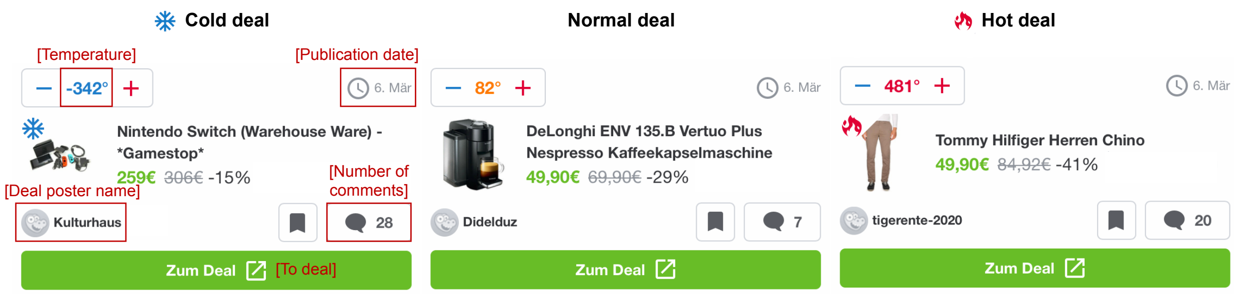

Figure 2: Examples of a Cold, Normal, and Hot Deal

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 newcomer 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 record the poster'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 text of the comment 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 (e.g., Malik et al., 2019). Although the exact methodology of the API is not disclosed, it has been shown that 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 sum of the three scores equals 1. We also collected data from each deal poster'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. We consider 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. Our measure of newcomer retention, *DealPosted*, is a binary indicator of whether users posted any deals within the 12 months after their first deal. We analyze the quality of subsequent contributions only for users who posted at least one deal in the 12 months following the first deal. We measure changes in the quality of contribution 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, Δ*DealTemp*. As alternative measures of quality, we measure the average deal temperature, *AvgDealTemp*, the average likelihood of users mentioning a price comparison in the descriptions of their subsequent deals, *AvgPriceComp*, and, if both the original price and discounted price are available, the average percentage discount, *AvgDiscount*.[6]

AvgDescLen captures the average description length of the subsequent deals over the 12 months after a newcomer's first deal. *DaysSecDeal* measures the time (in days) from the first to the second

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

deal. *AvgDescLen* reflects users' effort to produce subsequent deals. *DaysSecDeal* reflects users' general interest in posting another deal. We also control for the badges earned by users. *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 1,100 days (∼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.

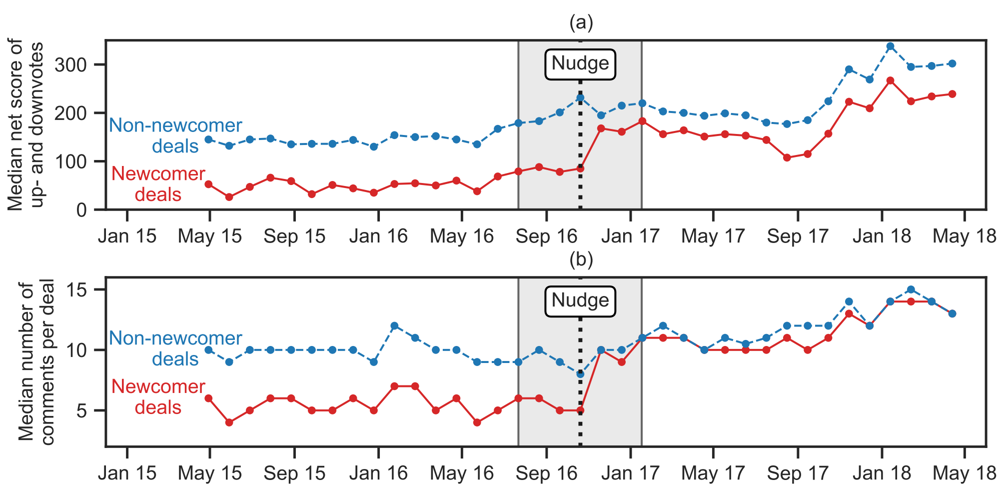

Figure 3: Newcomer vs. Non-Newcomer Deals in the Long Run (1,100 Days)

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 policy change).

Main Results

The model-free trends in Figure 3 do not account for the control variables that might confound the nudge effect. We use a DID strategy to identify the effect of the newcomer nudge on *Num-*

Comments and the three sentiment scores, *Positive*, *Neutral*, and *Negative*. 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 and the sentiment scores of the comments on deal i. *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 poster 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. The coefficients of the interaction term, *Newcomer*×*After*, are consistently positive and precisely estimated. 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 of implementation.[7] 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 general sentiment toward newcomer deals. We focus on the 90-day window as our preferred estimate.[8]

Validation

Robustness Checks. Table 3 reports several 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 above the mean (mean = 2.663, standard deviation = 9.886). In the even columns, we include deals posted by deleted, banned, or employed members (see Supplementary Appendix A). In Column (9), we use the percentage of negative words as an

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

[8] 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: Main Results

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. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

alternative operationalization of sentiment (Shen et al., 2015).[9] All of these estimations produce results consistent with the main estimations in Table 2, i.e., the nudge has aroused more responses and more positive sentiments from existing members on the newcomer deals.[10]

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

[10] 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.

Table 3: 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*. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

In Supplementary Appendix C, we show that the existing community members changed their behavior because the platform told them to be nice instead of noticing (via the nudge) that they were interacting with a newcomer. We make this inference by leveraging the fact that some newcomers revealed their newcomer status 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 after controlling for the dissemination of status.

Parallel Trends. The identification of treatment effect in DID is founded on the parallel trend assumption, that there is no pre-treatment difference between the treatment and control groups. 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 (i.e., "relative time model"):

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

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 helps identify whether a pre-treatment trend existed and whether and how the effect has changed after 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.

We present the estimation results in Table 4, which show that none of the pre-treatment coefficients of *Newcomer*×*Distance* is different from zero. Hence, the parallel trends assumption is unlikely to be violated. By contrast, all post-treatment coefficients for *NumComments* 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 the sentiment scores occur only after the policy change and that no spurious or erroneous associations exist.

Table 4: Relative Time Model

	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 5 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 5: 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 in Newcomer Deals. Given that our analysis uses a DID design with repeated cross sections (i.e., different deals posted before and after the intervention), 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 main 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.[11] We remove observations with the second deals posted after the policy

[11] We exclude second deals posted within one day of the first deal because we find a number of duplicates or near

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

Effect of the Nudge on Socialization Outcomes

We next consider the impacts of the nudge on newcomer retention and their quality of contributions. 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 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.

$$y_i = \beta_0 + \beta_1 Newcomer_i + \beta_2 Newcomer_i \times After_i + \beta_3 Tenure_i + \gamma_1 Badges_i + \gamma_2 Day_i + \varepsilon_i, \tag{3}$$

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

We first investigate the effect of the nudge on retention, measured by a binary indicator, *Deal-Posted*, 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. We find that newcomers in the post-nudge period are 4% more likely to post a deal in the 12 months after the first deal (p <0.01) than non-newcomers, indicating

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.

better retention of newcomers after the nudge. In Supplementary Appendix D, we show a similar pattern for commenting behavior.

Table 6: 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

Next, 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 are consistent.

Explanations

One possible explanation for the decline in Δ*DealTemp* is that the nudge "shelters" newcomers by inducing existing community members to pardon or gently correct their mistakes and upvote them. In the absence of the nudge, newcomers are less likely to experience this protection. In other words, the nudge might have caused a temporary shock to the first deals, but the subsequent deals go back to normal. Thus, we expect the temperature of deals posted after the first deal, *AvgDeal-Temp*, to be similar before and after the nudge. The results presented in Column (3) of Table 6 show 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 indicate that the net quality of subsequent deals by newcomers is largely unchanged, supporting the explanation that the change in Δ*DealTemp* in Table 6 may be attributed to the absence of the nudge on subsequent deals. In Supplementary Appendix E, we offer further qualitative evidence in support of this explanation.

We now explore alternative 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 difference between the first and second deal, *DaysSecDeal*. The former reflects the effort put into subsequent deals and the latter represents an indicator of 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 motivation has not changed.

The lenient behavior toward newcomers might reduce the quality of the information provided in the comments. The reduction can be problematic because newcomers are less likely to learn and, in turn, may fail to translate 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 (see 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 deal post, experience a more pronounced decline in $\Delta DealTemp$ between their first and subsequent deals. We find that the effect of the nudge exists for both experienced and inexperienced newcomers, measured as tenure and cumulative comments written up to the first deal (see 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 of each variable into low and high experience newcomers. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

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 large deal-sharing community. By exploiting a natural experiment on mydealz, we find that an intervention that reminds people to be more considerate to newcomers causes newcomer deals to receive more comments with a more positive sentiment. More importantly, consistent with the reinforcement effect, we find that newcomers are more likely to post another deal after the nudge, suggesting improved newcomer retention. However, the intervention has not affected the quality of newcomers' subsequent contributions.

Tendency to Support Newcomers

We find that the nudge shifted the existing community members' responses to newcomer posts to become more positive. The nuanced analysis in Supplementary Appendix C further shows that this effect is more likely caused by the extrinsic advice of the nudge to tell people to be nice instead of the intrinsic information about the newcomer status. This finding has important theoretical implications as it suggests that relying on insiders' intrinsic interest and responsibility to groom and develop newcomers may not be as effective in online social communities as in conventional organizations. To better model the newcomer socialization process and outcomes in the digital world, we might need to extend the socialization theories (Jones, 1986; Van Maanen & Schein, 1977) by explicitly accounting for the high propensity of attrition and weak-tie relationships commonly observed in online social communities. We might also need to establish the theoretical merits of parental measures such as a nudge with instructional nature as part of the newcomer 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., Adjerid et al., 2019; Matias, 2019). The nudge may be especially useful when organizational or community practices 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).

Community Response and Socialization Outcomes

The positive impact of the intervention on retention suggests that interacting with other members reinforces continued participation (Joyce & Kraut, 2006; Lampe & Johnston, 2005; X. Zhang et al., 2017). This finding informs the broader tension of whether active and committed community members are born (i.e., newcomers have an intrinsic commitment) or made (i.e., newcomers become committed through their interaction experience with existing members) (e.g., Panciera et al., 2009). We add to this theoretical discussion by contributing new empirical evidence from an online community, that feeling socially accepted by insiders can help entice newcomers to return independent of their intrinsic propensity to participate. Future research should explore which newcomers are more likely to benefit from the nice gestures of existing members to design more precisely targeted interventions.

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), but newcomers may also learn from negative experience (Wilhelm et al., 2019). Our empirical results show that the positive 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 the lack of task-relevant knowledge is the primary cause for quality not to improve, but it seems to be a tenable explanation as receiving nicer comments means the newcomers may not have motivation to learn beyond what they have seen in 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, 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 creating a more conducive environment for newcomers to learn and improve their contributions.

Generalizability to Other Communities and Future Research

Although we offer empirical evidence from a specific setting, a deal-sharing community, we believe our findings can be generalized to other communities where people join primarily for information exchange (see Ridings & Gefen, 2004) and where contributors must follow specific guidelines and policies to participate (Kraut et al., 2012). For example, when asking a debugging question on Stack Overflow, users should include a minimal workable example (MWE) so that other users can reproduce the problem. In such an environment, the nudge is likely to be effective because it makes other members more likely 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 itself may already be a place where members are inclined to show pro-social behaviors regardless of whether the platform tells them to be nice. Therefore, an intervention that provides protection may neither be a necessary nor an effective mechanism to retain new users. Overall, it is worthwhile to replicate our results in other contexts because the patterns of user participation can differ markedly between different types of communities (e.g., Nonnecke & Preece, 2000).

We conclude this paper by offering a few research directions. First, recent research has shown that people learn from the behavior of others in the same local space (Hou & Ma, 2022). Future experimental work can compare how individuals adjust their behavior in response to the nudge (as an institutional signal implemented by the platform) compared to others' public behavior, such as comments that have been posted in the same thread. For example, if others' public behavior is a stronger driver of behavior change, communities could think about encouraging specific users to address newcomers without implementing the nudge. Second, we cannot track people who saw the intervention but decided not to comment. It is impossible to separate the decision to participate from the decision about how to participate in our setting (see Matias, 2019). Therefore, an interesting future research is to analyze whether some people feel discouraged to comment after seeing the nudge intervention. If some experienced members shy away from commenting on newcomer deals due to the nudge, this might hurt the quality of discussions.

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