Motivation of User-Generated Content Contribution:
Social Connectedness Moderates the Effects of Monetary Rewards [1]

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ABSTRACT

The creation and sharing of user-generated content such as product reviews has become increasingly "social," particularly in online communities where members are connected. While some online communities have used monetary rewards to motivate product-review contributions, empirical evidence regarding the effectiveness of such rewards remains limited. We examine the possible moderating effect of social connectedness (measured as the number of friends) on publicly offered monetary rewards using field data from an online review community. This community saw an (unexpected) overall *decrease* in total contributions after introducing monetary rewards for posting reviews. Further examination across members finds a strong moderating effect of social connectedness. Specifically, contributions from less-connected members increased by 1,400%, while contributions from more-connected members declined by 90%. To corroborate this effect, we rule out multiple alternative explanations and conduct robustness checks. Our findings suggest that token-sized monetary rewards, when offered publicly, can undermine contribution rates among the most connected community members.

Keywords: user-generated content, monetary rewards, social connectedness.

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1. INTRODUCTION

User-generated content such as product reviews has become increasingly "social," in the sense that consumers draw content not only from the general community, but also from their own online social connections. Many review sites, including CitySearch, TripAdvisor, UrbanSpoon and Yelp, have endeavored to build connected review communities, and many such sites have partnered with Facebook to allow users to share reviews with their Facebook friends. The success of these efforts[2] is perhaps not surprising, since reviews by social connections tend to be more attractive than "anonymous" reviews due to the high level of trust and personal knowledge that make such recommendations more relevant (Brown and Reingen 1987; Feick, Price, and Higie 1986).

The low frequency of UGC contribution, however, remains a serious concern,[3] prompting review platforms to consider offering monetary rewards for consumer reviews (New York Times 2012a, b). Interestingly, while some platforms (e.g., Epinions and Refer.ly) make the rewards public, as dictated by recent FTC guidelines,[4] others offer incentive payments sub rosa (e.g., Angie's List and Seeking Alpha).[5] Still, platforms including Yelp and TripAdvisor choose to continue using non-monetary incentives, such as user feedback for their reviews (e.g., Yelp's "useful," "funny," or "cool" buttons) and platform recognition (e.g., Yelp Elites) to induce user-generated reviews (McIntyre et al. 2015).

The increasingly significant social aspect of UGC and the quite divergent use of monetary rewards prompt two research questions. Should online communities use monetary rewards to incentivize contribution rates among *connected* consumers? If so, are monetary rewards more effective for more-, vs. less-connected consumers? We address these questions using novel evidence from the field.

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[2] For example, Citysearch has seen a dramatic increase in registrations since implementing Facebook Connect: the number of daily registrations has tripled since its launch, and 94% of reviewers are sharing their reviews on Facebook. TripAdvisor now draws more than a third of new reviews from Facebook-connected users. In 2012 alone, one billion "open graph share actions" took place on the site, indicating that users are tapping their friends within TripAdvisor for information regarding properties, services, and locations.

[3] For example, only 1% of Yelp users are active contributors (Darnell 2011).

[4] The FTC guideline states: "If there's a connection between the endorser and the marketer of the product that would affect how people evaluate the endorsement, it should be disclosed." Source: https://www.ftc.gov/tips-advice/business-center/guidance/ftcs-revised-endorsement-guides-what-people-are-asking. Retrieved on May 10, 2015.

[5] Source: Personal invitations and offers received by the authors from the two companies.

Observe that a key feature of social UGC is that the core audience for a review usually consists of the contributor's social connections (e.g., "friends" or "followers") within the community. This social aspect of review sharing makes the decision to post a review quite a distinct one, in which the utility derived by a contributor from posting a review can be a function of her social connectedness. This observation, along with the literature review below, leads us to hypothesize that the member's level of social connectedness moderates her willingness to contribute in the presence of monetary rewards.

We provide empirical evidence for the key moderating effect of social connectedness utilizing data from a Chinese online social review community. We corroborate these findings by ruling out multiple competing explanations, and by conducting a series of robustness checks.

2. LITERATURE REVIEW

Monetary vs. Non-monetary Rewards. Promotional payments to consumers are extensively used in the offline world to induce many kinds of desired behaviors and to overcome procrastination. The idea of using monetary rewards to promote review contributions is a natural extension. Avery et al. (1999) set up a game-theoretical model of a market for product reviews, where the contributor bears the private costs of contributing reviews (e.g., the efforts for writing reviews and the risks of trying a product early), yet others can access these reviews for free. They show that introducing monetary rewards can overcome the free-riding problem and consequently induce an efficient level of product-review contributions. However, field-based empirical investigations into the effectiveness of monetary rewards remain sparse, and the results are mixed (see the review by Garnefeld et al. 2012).

Non-monetary Rewards in a Connected Online Community. Despite the significant costs to the authors of providing product reviews, online review communities that rely only on *voluntary* contributions often see nontrivial levels of reviewing. Hennig-Thurau et al. (2004) address this paradox by showing various types of *non-monetary* rewards that operate to motivate voluntary contributions. Specifically, their survey finds that voluntary contributions generate *social benefits* — e.g., to "help others with my own positive experience" and *reputation benefits* — e.g., "my contribution shows others that I am a clever customer." Hennig-Thurau et al. (2004) suggest that both monetary and non-monetary rewards drive review contributions. We argue, however, that monetary rewards may actually suppress intrinsic motives, and consequently, become ineffective or even counter-effective. First, monetary rewards may transform a "social market" into a "monetary market," thereby decreasing prosocial behaviors (e.g., Heyman and Ariely 2004). Reputation utility is also at risk after monetary rewards are introduced because unfavorable inferences might be drawn regarding whether the reviewer's true motivation is altruistic.[6] This has been referred to as the "crowding-out effect" of a small monetary reward (Frey and Jegen 2001), but has never been empirically investigated in the context of rewards for online reviews.

Social Connectedness Moderates Non-monetary Rewards. Informed by the fact that social connections are the main audience of a member's product reviews, we expect social connectedness to play a key moderating role in motivating UGC contributions. When members' contributions are driven purely by non-monetary rewards, the social benefits from review contributions are likely to increase with the size of the audience (e.g., Toubia and Stephen 2013; Zhang and Zhu 2011). Thus, we expect that when members are driven by social benefits, their willingness to contribute would increase with the number of social connections. Furthermore, reputation benefits from voluntary contributions are also likely to be amplified by a higher level of social connectedness. In the context of online communities (e.g., Facebook and Twitter), UGC contributions from more-connected community members usually have higher *visibility*. Therefore, any potential reputation benefits should be greater for more socially connected members, who can project to a larger audience.

Social Connectedness Moderates Monetary Rewards. Monetary rewards may also trigger a negative effect for members driven by a prosocial image, since being paid for a review might diminish their reputation. For potential contributors, this becomes a realistic concern because of the FTC's increasing enforcement of its guidelines, which puts the "exchange" between monetary rewards and review contributions under greater public scrutiny.[7] Benabou and Tirole (2006) further show that tension between monetary rewards and reputation benefits increases with the visibility of the action. Anticipating the potential negative inference regarding their ulterior motives, members whose actions are more visible are less likely to send an unfavorable signal about themselves. Benabou and Tirole (2006) refer to this as the "over-justification" effect of monetary rewards. Importantly, such a negative effect is most likely to arise for small monetary rewards.[8]

Within a connected online community, the visibility of an "exchange" between product review contributions and monetary rewards likely increases with social connectedness, which may decrease the effectiveness of such rewards for well-connected community members. To the best

[6] In the context of rewarded referrals, Verlegh et al. (2013) found empirical support that rewards lead recipient consumers to infer "ulterior" motives for the referral.

[7] For example, Seeking Alpha recently added a disclosure section, e.g., "I wrote this article myself, and it expresses my own opinions. I am not receiving compensation for it (other than from Seeking Alpha). I have no business relationship with any company whose stock is mentioned in this article."

[8] If sufficiently large, undoubtedly a monetary reward would have a positive effect on review production. However, that may not be the case for small or *token-sized* monetary rewards, which would be most feasible in practice. In the rest of the paper, a monetary reward always indicates a small monetary amount.

of our knowledge, however, no existing studies have examined the possible moderating effect of social connectedness for voluntary and incentivized product review contributions. We next present empirical evidence that social connectedness can indeed be an important moderator for the impact of monetary rewards.

3. EVIDENCE FROM A FIELD STUDY

Our empirical research context is an online social shopping community (OSSC). An OSSC is a virtual platform that integrates online shopping and the community sharing of UGC (e.g., product reviews). Examples of OSSCs in the U.S. include Airbnb, Foursquare, Kaboodle, Polyvore and TrendMe. OSSCs facilitate community members' generation and sharing of various types of content such as personal shopping lists, order histories, and product reviews, which are often cited as a major benefit of such communities for their members (New York Times 2011). Unlike traditional online retailers (e.g., Amazon), an OSSC allows its community members to connect with one another and be "friends."

Our data were obtained from an anonymous, and now defunct, OSSC based in Beijing, China (henceforth *the community*). The community hosted an online platform where consumers could find recreational services (e.g., ceramic studios, dance schools and DIY bakeries), write and share their views about the services, as well as connect with other members. Over the course of the observation period, the online community attracted a total of 11,430 registered consumers (i.e., members) and 2,456 sellers.

While free for members, the community charged affiliated sellers a percentage of the sales price for each order made through the community website. Each seller had a virtual storefront with standardized layouts containing product descriptions, as well as order and checkout pages. Most of the "products" were experience goods and were relatively expensive (equivalent to $1.20 – $220 US), so product reviews were an important information source for potential buyers. Sellers were strictly prohibited from providing any incentives (e.g., discounts or free services) for the product reviews.

Community members set up personal portals where they could create and update personal profiles, post product reviews, and join "circles" with other members sharing similar interests. Members also engaged in non-purchase discussions through a public forum by either initiating a new topic or replying to an existing one. A member could form social connections by sending an invitation to another member, and once the invitation was accepted, the two members were *friends* on the platform. In this study, we use *number of friends* as the measure of social connectedness. The distinction between friends and non-friends is very important from the perspective of product review sharing because a product review posted by any member was automatically pushed to all of her friends; in contrast, members who were not connected with the contributor would only find the same review when shopping at the seller's website.

Overview of the Field Study. During the first year of operation (January 2009 to December 2009), the community depended solely on voluntarily contributed product reviews, but became increasingly concerned about the decline in contributions. In hopes of reversing the decline in its member-generated contents, the community publicly announced that starting on January 1, 2010, it would offer a monetary reward for each product review posted. Immediately before introducing the monetary rewards, the focal community placed on the landing page of its website an announcement of its new policy. This announcement remained visible for the rest of the observation period. Thus, it is reasonable to assume that the offered monetary rewards were public knowledge to all community members. The reward was a cash-equivalent community credit worth approximately $0.25, redeemable at all affiliated sellers. The introduction of a monetary reward effectively divided the observation period into two regimes: a four-month *voluntary regime* from September 2009 to December 2009; and a four-month *paid regime* from January 2010 to April 2010. This intervention provides a good opportunity to empirically assess the differential effect of monetary rewards across members in this community.

Data. The online community was launched in January 2009; however, the data collection was not systematic until September 2009. The data we use span an eight-month period, from the beginning of September 2009 to the end of April 2010. The community provided us with a random sample of 2,286 members (approximately 20% of all registered members). For each member, we have the detailed records of activities that include review contributions, orders and logins. The community also tracked each member's friend-network formation over time from January 2009. To obtain the estimation sample, we took two steps to eliminate data unsuitable for this research. First, the regime change may have attracted members who are more interested in the monetary reward. To avoid this possible bias, we included only members who joined *before* January 1, 2010. Second, we focus on active members, i.e., those who participated in at least one of the following community activities during the data period: logins, discussions, orders, and product review postings. Inactive members were excluded because without any activity on the website, it is not feasible to infer their responses to monetary rewards. Table 1 provides the summary statistics.

[Place Table 1 about here]

The resulting estimation sample contains ~25,000 weekly observations from 878 active members. For each week t, we observe whether member i provided a review ($Review_{it} = 1$) or not ($Review_{it} = 0$), her total number of reviewing weeks up to t ($CumReview_{it}$), and her non-reviewing activities, which include logins ($Login_{it}$), orders ($Order_{it}$), and community discussions ($Discuss_{it}$). An average member posted reviews in approximately four percent (4%) of all weeks.[9] A typical member logged in to the website 6.5 times a week and engaged in 0.15 community discussions, on average, although the large standard deviations of login frequency (25.6) and discussions (1.48) indicate substantial variation in terms of engagement level with the community. The average order rate was low (0.003). At the time of the regime change, community members had an average of 1.64 friends.

We first observe that at the aggregate level, the introduction of monetary rewards failed to reverse the decline in the contribution rate: compared with the 4-week pre-reward period, the total review frequency in the 4-week post-monetary reward period decreased from 0.080 to 0.045, a 43.8% drop. To examine the possible moderating effect of social connectedness, we classify members of the community into four subgroups, based on their friend counts at the time of the regime change. Among the 878 members, 689 had zero friends (we call them "loners"), 80 members had 1-2 friends, 44 members had 3-5 friends, and 65 members had more than five friends (we call them "socialites"). For each of the four subgroups, we compute the average contribution during the four weeks prior to and after the introduction of payment for reviews. The results are presented in Figure 1, where the x-axis represents the subgroups, defined by the number of friends; and the y-axis plots the average number of reviews. This chart shows that, prior to the rewards, people with more friends tended to offer more reviews; however, that reversed after the monetary rewards started.

[Place Figure 1 about here]

To quantify both the main and moderating effects of social connectedness in the members' responses to the monetary reward introduction, we develop a difference-in-difference (DID) model.

Model. The dependent variable is d_{it}, where:

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[9] We find that the pattern of review posting in our focal community is similar to that reported in larger online social networks. Specifically, among all community members in the data sample, 85.1% contributed zero reviews, 12.1% contributed 1-10 reviews, and 2.8% contributed more than 10 reviews. This pattern is in line with the "90-9-1" principle (e.g., Ochoa and Duval 2008; Shriver et al. 2013), which states that 90% of users do not actively contribute to the site, 9% of users contribute occasionally, and 1% of users are very active contributors. This implies that although the focal review network is modest in size, it is similar to those larger counterparts studied previously.

$$d_{it} = \begin{cases} 1, \text{if member } i \text{ posts a review in week } t \\ 0, \text{otherwise} \end{cases} \quad (1)$$

This decision is based on a latent-utility:

$$\begin{aligned} U_{it} = \beta_{0it} + \beta_1 PostReward_t + \beta_2 CumReviews_{it} + \beta_3 Tenure_{it} \\ +\beta_4 Friends_{it} + \beta_5 PostReward_t \times Friends_{it} + \beta_5 d_{it-1} + \epsilon_{it} \end{aligned} \quad (2)$$

In this setup, $PostReward_t$ takes a value of 1 if week t is after the introduction of the monetary reward. β_1 captures the average effect of the monetary reward. $CumReviews_{it}$ counts the cumulative number of reviews provided by *i* up to week *t*, which captures a possible fatigue effect coming into play after members started posting reviews. $Tenure_{it}$ refers to the number of weeks since *i* joined the community, which captures the change in the contribution probability over time before a member posted the first review. The two key variables are the number of friends ($Friends_{it}$) and the interaction term ($PostReward_t \times Friends_{it}$). The parameter of $Friends_{it}$ captures the average main effect of the number of friends on a member's review offering probability. As discussed earlier, given that an individual's reviews will be automatically shared with his/her friends, the number of friends is a proxy for the size of the audience, which has been identified as an important factor influencing whether or not to offer a review (Zhang and Zhu 2011). The parameter for the interaction term captures the moderating effect of friends in influencing people's responses to the monetary reward. In addition, to capture the possible state dependence in product-review behaviors over time, we incorporated a review dummy into the last period by the same member. Finally, weekly level fixed effects are included to capture any possible week-specific effect (e.g., a week with a long weekend may be a relatively popular time to write a review).

The main and moderating effects of the number of friends are the focus of our study. However, it is possible that some common factors at the individual level might drive both the decisions of "the number of friends" and "whether to offer a review," which would make the number of friends an endogenous variable. To allow for such a possibility, we use an instrumental variable approach with "the number of circles" variable as an instrument[10].

Assuming that ϵ_{it} follows a standard normal distribution, we obtain a Binary Probit model with an endogenous regressor, which is then estimated with the maximum likelihood method provided in STATA. The second column of Table 2 summarizes these results. The estimate for

[10] The validity of the instrument is discussed in detail for the Hierarchical Bayes model in the Online Appendix.

β_1, the response to the monetary reward, is -1.27, statistically significant at the .05 level.[11] The parameter estimate for $Tenure_{it}$ is negative (-0.053) and statistically significant, indicating a fatigue effect. In contrast, the parameter estimate for $CumReviews_{it}$ has a positive and significant estimate. Combined, these two parameters suggest that over time, a member is less likely to start posting reviews. However, the more reviews a member has written, the more likely she is to post another review. The estimated coefficient of ($Friends_i$) is positive, with $\beta_4 = 0.050$; further, the coefficient of $PostReward_t \times Friends_{it}$ is negative, with $\beta_5 = -0.077$; and both are statistically significant. These two parameters indicate that members with more friends have a higher baseline propensity to offer reviews, compared to those with fewer friends. However, when a monetary reward is offered, members with more friends responded more negatively in their review frequency. In other words, the estimation results show that the number of friends has a positive impact on the baseline probabilities of posting reviews; in the meantime, it moderates the effect of the monetary reward. Finally, the parameter estimate for a lagged review is positive and statistically significant, indicating positive state dependence in the review contribution tendency.

Robustness Checks. To ensure the reliability of the empirical results, we conducted a number of robustness checks. [12]

a) Alternative cutoff dates. To validate the DID model, we repeated the analysis with two alternative cutoff dates. The first one is the week right before, and the second is the week right after the week when the monetary rewards were introduced by the focal community. We found two main results. First, the model fit based on either of these alternative cutoffs is significantly worse than that of the main model.[13] These additional results are consistent with the monetary rewards, taking effect in the week prescribed by the focal community.

b) Individual choice model. To measure the effects more precisely, we employ an individual-level Logit choice model estimated within a Hierarchical Bayes (HB) framework, accounting for consumer heterogeneity and possible endogeneity. The HB model confirms our finding that social connectedness moderates monetary rewards for generating social contributions, as found in the

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[11] While it is tempting to conclude that monetary rewards had a negative impact on a member's review contributions, this result should be interpreted carefully because (1) the "design" of the field study did not have a control group and (2) this simple DID model does not control for heterogeneity.

[12] We thank the reviewers for their very helpful suggestions in conducting these robustness checks.

[13] The Akaike Information Criteria (AIC) for these three models are: 5046.6(main model), 5071.8 (the model with the placebo cutoff date set at week "-1") and 5112.4(the model with the placebo cutoff date set at week "+1").

model-free and difference-in-difference analyses. The reader is referred to Part 1 of the Online Appendix for the details of the model specifications and results.

c) Separate estimation of members with vs. without friends. The main analysis pooled members with friends and those with no friends. As an alternative, we split the estimation sample into those with or without friends, and estimate the model on each group separately. As presented in the third and fourth columns of Table 2, the results echo those of the main model qualitatively. In particular, for the group with no friends, the estimated response to the reward is positive and statistically significant (1.06), indicating that members with no friends respond to the monetary reward positively. For the group with friends, the estimate for the reward parameter is positive, but not statistically significant (mean 1.399, standard error 0.711). The estimate for the interaction term is negative (-0.051) and statistically significant, showing that the rewards diminished the review posting frequency for more connected members.

d) Estimation based on active contributors. Second, members who posted reviews may be different from those who were "active" (e.g., placed an order), yet never posted any reviews. Thus, we estimate a model using the subsample of active review contributors, defined as members who contributed at least one review in the observation period. The results are presented in column 5 of Table 2. We find that the results qualitatively echo those of the main model.

e) Visibility as a function of active friends. The main analysis assumes that the "visibility" of review posting is a function of the number of friends before the regime change. A possibly better proxy for visibility is the number of *active* friends, since review posting is less likely to be observed by members who were not active. Thus, we re-compute the variable by excluding friends who were inactive during the observation period. We find that the new variable is highly correlated with the original variable (correlation is 0.98). Therefore, it is not surprising that our estimation, based on the new variable, produced almost identical results, as listed in the last column of Table 2.

[Place Table 2 about here]

The above analysis demonstrates the robustness of the moderating effect of "the number of friends" on the response to monetary rewards. Next, we examine possible alternative explanations.

Alternative Explanations. Following Remler and Ryzin (2010), we examine three categories of alternative explanations: a) chance factors, b) extraneous factors and c) history effect.

a) Chance factors. Bertrand et al. (2004) show that in panel data, ignoring serially correlated outcomes with a one-shot treatment (as in our context) may lead to false significant estimates of the treatment effect. We follow the suggestion by Bertrand et al. (2004) and collapse the data into "before" and "after" periods and check the before-after differences across the friend groups. We find that across the friend groups, the contribution rates *significantly* decreased (increased) for socialites (loners), as has been demonstrated in Figure 1.

An additional chance factor concern is regression to the mean (RTM), i.e., the high (low) level of voluntary contributions by more- (less-) connected community members was a result of sheer chance, and these levels simply reverted to a lower (higher) level after the regime change. Typically, RTM is a threat when a pre-treatment measure is used to assign experimental treatments to groups, when there is self-selection, or when there is some pre-treatment difference in the groups in terms of the dependent variable (i.e., frequency of review writing). Figure 2 highlights the differential change in contributions around the reward introduction (week 0), benefitting from the panel perspective of the data. Although there was a mild decline in the review frequency for socialites before the introduction of the reward, the dramatic shifts in review frequency only at week 0 are evident - downward for the socialites, but upward for the loners. This seems to rule out regression to the mean as an alternative explanation for these shifts (or else the shifts would have happened in any of the other prior weeks to the announcement, but they did not).

[Place Figure 2 about here]

b) Extraneous factors. First, we consider the possible *signaling* effect of monetary rewards (Gneezy et al. 2011). Specifically, the announcement of a reward itself may have suggested to community members that writing a review is a more difficult task than they may have previously thought. Second, the change in review frequencies may have been driven by the change in community engagement levels, which can be measured by the average login and order frequencies around the regime change. Third, based on Social Exchange Theory (Gatignon and Robertson 1986), more-connected contributors may have felt more obliged to increase their efforts, which might also have reduced their willingness to post reviews in the first place. To test for these possibilities, we conducted several checks that boil down to analyzing the following empirical questions: Did the number of other activities, such as weekly logins and orders, change around the regime switch? Did the effort put into writing a review change (given that one was written)? As detailed in Part 2 of the Online Appendix, none of these effects showed any similarity to the one observed for the number of reviews written.[14]

[14] We thank the Associate Editor's suggestion to check this.

c) *History effect*. One possible alternative explanation to the data patterns is some unobserved extraneous factor that happened along with the monetary rewards, leading to changes in the members' behaviors and their participation in the community. From the perspective of members' decisions on community engagement, the decision calculus for participating in discussions and offering product reviews is very similar. We exploit the fact that the monetary reward was offered only for product reviews, but *not* for community discussions. Before the regime change, the correlation between product reviews and discussions was positive and significant (*rho* = 0.36, $p<0.001$). However, taking again the panel view of the data, Figure 3 shows that the pattern is very different for uncompensated community discussions. Specifically, discussions slightly increased in the 4 weeks after payment (for reviews) started for well-connected community members (e.g., those with >5 friends), but decreased in the 4 weeks after the regime change for less-connected members (with 0 friends).[15]

[Place Figure 3 about here]

Combining a), b) and c), the analyses confirm that it is the introduction of monetary rewards, rather than changes in engagement factors (e.g., logins, purchases, and community discussions), that led to significant changes in the review posting frequency.

Analysis on Review Efforts. Preceding analyses have focused on changes in review contributions after a regime change. A natural question is, to what extent does the introduction of monetary rewards affect the efforts that were spent writing the reviews? We investigate this question by measuring both (1) the length of the reviews, and (2) the perceived efforts and helpfulness of the reviews around the regime change. As detailed in Part 2 of the Online Appendix, we examine the impact of monetary rewards on the lengths of the reviews contributed (measured by the numbers of characters in the reviews). We find that the introduction of the monetary reward had a negative and significant impact only on the contribution frequency, but not on the review length by community members once they decided to contribute. To measure (2), we hired two research assistants, both of whom are native Chinese speakers and are blind to our research questions. The research assistants independently read the texts of 1,500 product reviews in the estimation sample

[15] Note that this is essentially a "falsification check" (e.g., Sudhir and Talukdar 2015). Granted, even this test does not rule out every possible history effect; yet, for a history effect to be a true threat, it would have to (1) interact with the number of friends for the review contributions in the hypothesized direction, (2) but not interact with the number of friends for community discussions. An alternative explanation other than the effect of a monetary reward seems to be unlikely.

and rated the reviewers' efforts in writing the reviews, as well as perceived review helpfulness on 1-7 Likert scales. We find that conditional on contributing a review, after the introduction of the monetary reward, the amount of effort put forth by members without friends significantly decreased (M_{before} = 4.82, M_{after} =4.46, M_{diff} = 0.36 , p<.05). Similarly, the perceived helpfulness of the review also decreased (M_{before} = 5.39, M_{after} =4.92, M_{diff} = 0.47, p <.05). These results are interesting, but not quite surprising in retrospect. Recall that the focal community's policy is that monetary rewards are given to all contributed reviews, without stipulating any requirements for the contributed content. Such a policy may have likely induced a "transactional" mindset (e.g., Heyman and Ariely 2004) for loners, who might have focused on getting a good deal for the transaction, that is, a low cost of effort per unit of reward. In contrast, among members who are socially connected, the monetary reward hardly had any effect on effort (M_{before} = 4.75, M_{after} = 4.79, M_{diff} =0.04, p>0.60), or the perceived helpfulness of the review (M_{before} = 5.08, M_{after} =5.14, M_{diff} = 0.06, p >0.50). These results suggest that the "transaction mindset" effect seems to have had no significant impact on the socially connected, and their contributions continued to be driven by intrinsic motivations (e.g., helping others). These results also allow us to conclude that there is no support for the alternative explanation that members with friends decreased their contribution because of the higher level of effort implied.

4. SUMMARY AND LIMITATIONS

To summarize, this study allowed us to examine product-review contributions within an online community and the heterogeneous responses to a monetary reward. Our main finding was twofold. More-connected members contribute more often when the community relies purely on intrinsic motivation. However, the token-sized monetary rewards are motivating for members with few social connections, but demotivating for well-connected members. In other words, monetary rewards proved to be counter-effective for those most active contributors! A further problem facing the platform is the possible decrease in effort put forth by the loners when they finally did write a compensated review. In retrospect, our results provide a possible explanation for why platforms paying public cash rewards (Epinions and Refer.ly) have closed down, and why few existing platforms publicly offer monetary rewards for review contributions. Platform managers would be better advised to provide a private monetary reward only to members who have few connections on the platform, as this proves to be most effective.

We note that our field study has several contextual features that are conducive to the negative effect of monetary rewards on the most connected community members. First, the "push to friends only" design of the community is a feature shared by major social networks (e.g., Facebook and Twitter), but not all social networks. Second, the public introduction of a monetary reward is more likely to trigger reputational concerns than privately offered rewards. Third, a *token-sized* monetary reward was offered, which is more likely to have a counter-effect than a large monetary reward (Benabou and Tirole 2006).

In addition, our study has a number of limitations, providing direction for future research. First, in the absence of a *direct measure* of motivation from consumers, the *number of friends* is a surrogate for some underlying set of motivations. Second, future research can examine the effectiveness of larger-than-token-size monetary rewards, or other types of non-cash incentives, such as free products (e.g., Stephen et al. 2012). It would also be interesting to conduct controlled field experiments to examine when monetary rewards are "sufficiently large" to induce across-the-board increases in review contributions. A well-designed experiment would also be able to identify the main effect in addition to the interaction effect. Third, more sophisticated text analysis methods (e.g., Lee and Bradlow 2011) can be leveraged to understand how introducing monetary rewards may affect the content of reviews. Finally, the online community that we studied was relatively small and arguably idiosyncratic. Thus, caution is advised about generalizing our results, and future research should investigate whether tie strengths are weaker in larger communities (e.g., Facebook), and whether tie-strengths among community members further moderate the negative effect of monetary rewards.

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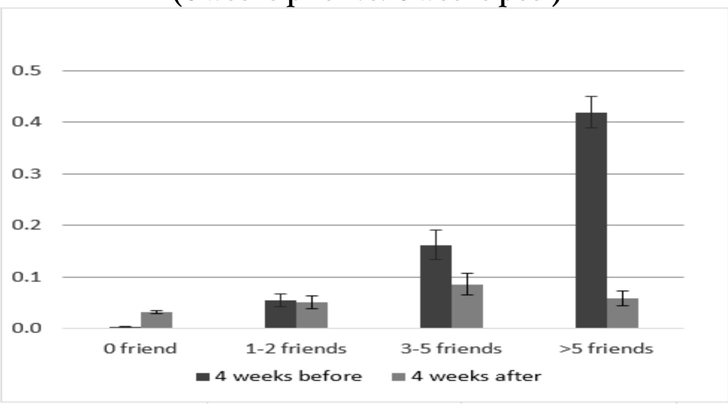
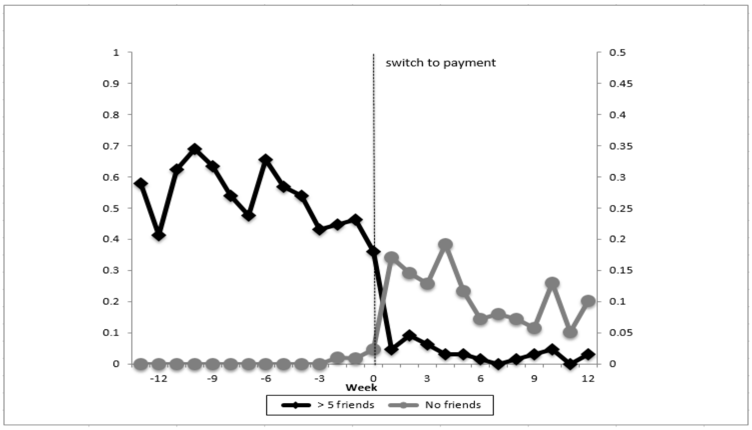
FIGURE 1
Average Review Production by Number of Friends
(4 weeks prior vs. 4 weeks post)



Note: High-low indicators are +/- one standard error.

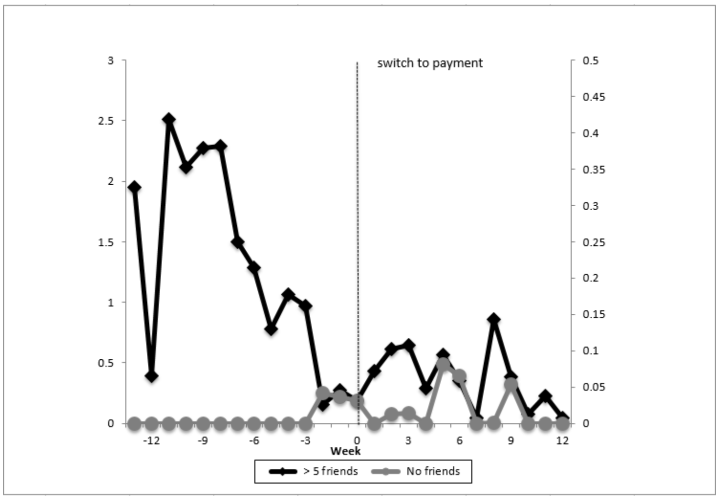
FIGURE 2
Average Review Frequency by Number of Friends and Week



Note: Left axis for the group with > 5 friends; Right axis for the group with no friends.

FIGURE 3

Average Community Discussions Frequency by Number of Friends and Week



Note: Left axis for the group with > 5 friends; Right axis for the group with no friends.

TABLE 1 Summary Statistics and Correlations

	Mean	Std. Dev.	V1	V2	V3	V4	V5	V6	V7	V8	V9
			Correlations								
V1: Review dummy ($Review_{it}$)	0.04	0.19	1.00								
V2: Cumulative reviews ($CumReviews_{it}$)	0.98	2.33	.267	1.00							
V3: Number of logins ($Login_{it}$)	6.49	25.6	.240	.610	1.00						
V4: Number of orders ($Order_{it}$)	0.003	0.070	.117	.119	.147	1.00					
V5: Community discussions ($Discuss_{it}$)	0.162	2.28	.350	.128	.051	.028	1.00				
V6: Number of friends ($Friends_{it}$)	2.19	7.71	.270	.679	.860	.136	.056	1.00			
V7: Number of circles ($Circle_{it}$)	1.54	5.14	.299	.676	.689	.132	.105	.716	1.00		
V8: Tenure (weeks) ($Tenure_{it}$)	14.54	9.15	-.138	.232	0.096	.0004	-..063	.009	0.080	1.00	
V9: Post-Reward dummy ($PostReward_t$)	0.75	0.43	-.189	.043	-..053	-.018	-.071	-.075	-.081	.617	1.00

Note: All correlations are significant at the p < .01 level.

TABLE 2 Estimation Results

	Main model	Robustness check (c1) Model based with members without friends	Robustness check (c2) Model based with members with friends	Robustness check (d) Model with active contributors	Robustness check (e) Main model, with active friends
Intercept	-1.566(0.131)***	-2.953(0.172)***	-1.165(0.141)***	-1.310(0.140)***	-1.584(0.131)***
$Friends_{it}$	0.050(0.007)***	--	0.044(0.009)***	0.048(0.008)***	0.064(0.010)***
$PostReward_t$	-1.268(0.587)**	1.061(0.179)***	1.207(0.671)	-0.696(0.493)	-1.260(0.601)**
$PostReward_t \times Friends_{it}$	-0.077(0.008)***	--	-0.051(0.009)***	-0.070(0.008)***	-0.078(0.007)***
$CumReviews_{it}$	0.212(0.010)***	0.668(0.032)***	0.244(0.016)***	0.155 (0.011)***	0.209(0.010***
$Tenure_{it}$	-0.053(0.005)***	-0.045(0.004)***	-0.165(0.012)***	-0.057(0.005)***	-0.054(0.005)***
Lag Review	0.277(0.077)***	-0.386(0.181)*	-0.031(0.089)***	0.107(0.071)	0.256(0.079)***

Note: * p < .05 level; ** p < .01 level; * p < .001 level.

Note: In Robustness check (c2), we replaced $Friends_{it}$ with $Friends_{it} - 1$ so that the main effect $PostReward_t$ captures the impact of monetary rewards at zero friends.

Appendix A Hierarchical Bayes Model

Results from the DID models in the text consistently show a moderating effect in the "number of friends" variable on community members' review posting decisions, before and after the introduction of the monetary rewards. These models do not account for unobserved heterogeneity. To do that, we developed a Hierarchical Bayes (HB) model, which is detailed below.

1.1. Model Specification

To quantify the influence of the monetary reward on review contributions at the individual level, we developed an individual-level Binary Logit model, cast in a HB framework with two levels. The top level captures the drivers of each member's decision to post a product review, while allowing for individual-specific parameters. The lower level explains the variations across the individual-level parameters by connecting them with observed characteristics, particularly social connectedness.

Top-level model. At this level, the dependent variable is d_{it}, where:

$$d_{it} = \begin{cases} 1, \text{if member } i \text{ posts a review in week } t \\ 0, \text{otherwise} \end{cases} \quad \text{(A1)}$$

This decision is based on a latent-utility:

$$U_{it} = \beta_{0it} + \beta_{1i} PostReward_t + \beta_{2i} CumReviews_{it} + \beta_{3i} Tenure_{it} + \epsilon_{it} \quad \text{(A2)}$$

The latent utility is conditioned on whether week *t* is after the introduction of rewards ($PostReward_t$), possible fatigue effects surrogated by the cumulative number of reviews provided ($CumReviews_{it}$) and the number of weeks since the member joined the community ($Tenure_{it}$). It also includes the base level (β_{0it}), which captures all of the other individual-time specific factors beyond those mentioned above. However, β_{0it} will exhaust the degree-of-freedom in the data, and cannot be identified. We thus decompose it into two components:

$$\beta_{0it} = \beta_{0i} + \beta_{0t}$$

where β_{0i} captures the baseline review contribution by member *i*, and β_{0t} captures any possible week-specific effect (e.g., perhaps a week with a long weekend is a relatively popular time to write a review).

Assuming ϵ_{it} follows the Type I extreme-value distribution, one arrives at the familiar logit formulation for the probability of writing a review:

$$P(d_{it} = 1) = \frac{\exp(V_{it})}{\exp(V_{it}) + 1} \quad \text{(A3)}$$

where V_{it} is the deterministic part of the latent utility in equation (A2), or, $V_{it} = U_{it} - \epsilon_{it}$

Lower-level model.

The lower-level model connects each individual's β_i-coefficients from the top level to that member's observed variables, therefore capturing any systematic differences of the four parameters across individuals. Among these four parameters, we are particularly interested in explaining the differences among members' baseline willingness to contribute (β_{0i}) and their responses to the monetary reward (β_{1i}). The key variable in the lower-level model is the member's level of connectedness (i.e., number of friends), which enables the test of possible moderating effects. As control variables, we also include two measures of engagement: log of the average number of logins, $ln(AvgLogin_i)$ and the average number of orders $ln(AvgBuy_i)$: both are strongly correlated with review posting decisions; yet, the correlation between weekly log-ins and orders is moderate, at 0.147 (Table 2 in the article). The key variable in this level is $ln(Friends_i)$, the log of the number of friends count.

Also included is one additional equation to correct for potential endogeneity related to the $ln(Friends_i)$, possibly being correlated with the unobservable errors at the lower level. To address such a potential endogeneity issue, we use the log of the number of circles a member affiliates with $ln(Circles_i)$ as an instrumental variable for $\ln(Friends_i)$. We choose this variable as an instrument because it is correlated with $ln(Friends_i)$: members who participate in more circles are more likely to form connections with other community members who have similar interests. One possible concern regarding this instrument is that it could also directly influence the response to monetary rewards at the individual level in the first part of the lower level model (equation (A4) below), in addition to its influence on $\ln(Friends_i)$, the potentially endogenous variable. To test this possibility, we conducted an analysis based on Conley et al. (2009), discussed in Part 1.2. We find that after controlling for the "number of circles" variable's influence on "number of friends," it does *not* have statistically significant influence on the dependent variables in equation (A4) and therefore, is a valid instrument.

To summarize, the lower level model includes two parts: (a) the four correlated multiple regressions connecting the parameters $\{\beta\}_i$ from the upper level model with the number of friends for each member, while controlling their level of participation; and (b) the equation describing the potential endogeneity of the "number of friends" variable. The error terms across all models in (a) and (b) are jointly distributed with multivariate normal distributions, allowing correlations among all these error terms. Using the seemingly unrelated regression approach, we estimated the parameters and the covariance matrix among all five equations from equations (A4) and (A5).

$$\begin{bmatrix}\beta_{0i}\\ \beta_{1i}\\ \beta_{2i}\\ \beta_{3i}\end{bmatrix} = \begin{bmatrix}\delta_{01} & \delta_{02} & \delta_{03} & \delta_{04}\\ \delta_{11} & \delta_{12} & \delta_{13} & \delta_{14}\\ \delta_{21} & \delta_{22} & \delta_{23} & \delta_{24}\\ \delta_{31} & \delta_{32} & \delta_{33} & \delta_{34}\end{bmatrix} \begin{bmatrix}1\\ \ln(Friends_i)\\ \ln(AvgLogin_i)\\ \ln(AvgBuy_i)\end{bmatrix} + \begin{bmatrix}\zeta_{0i}\\ \zeta_{1i}\\ \zeta_{2i}\\ \zeta_{3i}\end{bmatrix} \tag{A4}$$

$$\ln(Friends_i) = \theta_0 + \theta_1 \ln(Circles_i) + \theta_2 \ln(AvgLogin_i) + \theta_3 \ln(AvgBuy_i) + \eta_i \tag{A5}$$

$$\begin{Bmatrix}\zeta\\ \eta\end{Bmatrix} \sim N(0, \Gamma)$$

The right hand side of equation for endogeneity correction consists of not only the "number of circles" variable, but also the other two variables indicating the level of involvement (average logins and orders), which are necessary to obtain correct estimates (Greene 2008, p. 319, Wooldridge 2002, p. 91).

1.2. Plausibly Exogenous

Our choice of IV faces the common problem for all instrument variables: *conceptually*, it is impossible to rule out *all* possible correlations between the IV and the error term. However, the econometrics literature on less-than-perfect instruments (e.g., Angrist et al. 2003; Imbens 2003; Rosembaum 2002) shows that the validity of an IV can be *econometrically* examined through a sensitivity analysis on how the bias of the IV estimator relates to the error term.

Specifically, two conditions are necessary for a valid IV (e.g., Greene 2008, p. 316; Cameron and Trivedi 2005, p. 100). First, it needs to satisfy the exclusion restriction; second, it needs to be a strong instrument.

Conley et al. (2012) demonstrate that it is possible to make informative inferences regarding the parameters of a potentially endogenous variable, even when the first condition (exclusion restriction for the IV) is relaxed; that is, the instrument only needs to be *plausibly exogenous*. Furthermore, the strength of the instrument can be evaluated by checking the correlation between the IV and the endogenous variable using the parameter estimates in the model. In the following, we demonstrate that the IV in this case satisfies both conditions using the full-Bayesian approach of Conley et al. (2012). This extension is natural for our model, which is already cast in the hierarchical Bayes framework. The Conley et al. (2012) approach can also be used to gauge the extent to which the exclusion restriction is relaxed. Practically, this is achieved by incorporating the chosen instrument into the main model along with the potentially endogenous variable. In this setup, if the IV strictly satisfies (violates) the exclusion condition, its parameter will be 0 (non-zero).

Practically, the model above is not identified. Therefore, we need to set an informative prior regarding the distribution of the parameter γ. As suggested by Conley et al. (2012), we use a normal prior centered at zero. The exclusion restriction implies that the estimated values for γ_1, γ_2 and γ_3 are all zeros. If they are not, then the deviations from zeros indicate the severity of the violation.

Based on equation (A5), we estimate our model with two different priors regarding the parameters γ_1, γ_2 and γ_3. In both estimations, we let the priors follow zero-mean normal distributions. In the first estimation, the standard deviation of the prior is set to be small (1). In the second estimation, we use a rather uninformative prior for the γ parameters and set the standard deviations to be large (100). Table A1 shows the mean estimates of the parameters, as well as the 95% highest posterior density (HPD) regions of these estimates, for the two alternative prior distributions. Comparing the estimates and prior distributions, we noticed, as expected, that when the prior is more restrictive, the posteriors of these estimates are closer to the prior. When the prior is less restrictive, the posteriors of these estimates are more different from the prior distribution. However, in both cases, the posterior distributions of these parameters are all centered around 0, and the estimates are not statistically different from 0. According to Conley et al. (2012), these results indicate that the IV in this model does not violate the exclusion restriction.

Having demonstrated that the instrument does not violate the exclusion restriction, we next check the strength of the instrument using the estimated parameter of the instrumental variable in our model. Results show that when the prior for the γ parameters is $N(0,1)$, the parameter estimate and its 95% HPD region for the IV are 0.9953 and (0.93,1.06); and when the prior is $N(0,100)$, the estimate and 95% HPD region for the IV are 0.9939 and (0.93,1.06). To summarize, in both cases, the estimates for the IV parameter are almost identical, and they are both statistically significant, which demonstrates the strength of our IV. Based on these results, we conclude that the instrumental variable we used satisfies both conditions for being *plausibly exogenous*. Therefore, it is a valid instrument.

[Place Table A1 about here]

1.3 Estimation Procedure and Results

To estimate all of the model parameters simultaneously, the full information likelihood is

$$f_1(Y|\{\beta_i\}) \times f_2(\{\beta_i\}|friends, \Delta, \zeta) \times f_3(friends|\theta, \eta) \times f_4(\{\zeta, \eta\}|\Gamma) \times f_5(\{\Delta, \theta\}) \times f_6(\Gamma)$$

In the above equation, f_1 is the likelihood related to the standard heterogeneous logit model; f_2 is for the hierarchical regression specified in equation (A4)[16]; f_3 reflects the endogeneity correction from equation (A5); f_4 is the setup that estimates equations (A4) and (A5) together, while allowing their error terms to be correlated. Finally, f_5 and f_6 are the prior distributions specified below.

The prior of all parameters δ, θ in the lower-level model (equations (A4), (A5)) are specified as a joint MVN distribution with a mean of zero and a relatively large variance (100). The prior for the covariance matrix of the error terms Γ is an Inverted-Wishart with $n_0 = 7$ degrees of freedom so that the scale matrix $V_0 = 7I$, where *I* is the identity matrix.

$$\{\Delta, \theta\}^{prior} \sim MVN(0,100I)$$

$$\Gamma^{prior} \sim IW(7,7I)$$

Using the Markov Chain Monte Claro method, we obtain all of the model parameter estimates simultaneously. Next, we present the model results in detail.

The Top-Level Model

The first column in Table A2 presents the population level mean estimates. The 95% HPD regions from the marginal posterior distributions are listed in the parenthesis. In the first column, the intercept β_{0i} indicates the relative baseline contribution level of review posting. This estimate of the population mean is negative (-5.750) and statistically significant, indicating that most members contribute product reviews relatively infrequently.

The estimate for the population mean of β_{1i}, the response to the monetary reward, is -0.579. Its 95% HPD region includes 0; however, this does *not* mean that monetary rewards have no impact on a member's review contributions. Figure A1 plots the histogram of the individual-level parameters. It shows that a large group of members have positive response estimates, but a smaller group of members have negative responses, somewhat canceling each other out at the aggregate level.

<Place Figure A1 about here>

The last two parameters in the first column of Table A2 capture the effect of cumulative reviews and tenure. The estimate of the population mean for the cumulative review is negative (-0.076)

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[16] Where Δ refers to the matrix of δ's in equation (A4).

and statistically significant, indicating a fatigue effect. This fatigue effect comes into play after members started posting reviews, which confirms the literature (Figuieres et al. 2009). Before a member posted the first review, the change in contribution probability was captured by the "tenure" variable, which has a positive estimate. Finally, the estimated β_{0t} demonstrates a general downward sloping trend over time in posting. The results above have all been established after controlling for such a trend over time.

The Lower-Level Model

The lower-level model connects the individual-level estimates obtained from the top level model with individually measurable characteristics. The results are presented in columns 2-5 of Table A2.

Column 2 lists the intercept estimates for the four regressions in the lower-level model (equation (A4)). These regressions are correlated through the error terms. Of focal interest is column 3, which shows the estimates for $ln(Friends_i)$. This variable enters each of the four regressions in the lower-level model, where each β is treated as a dependent variable. The positive estimates in the first row δ_{02} =1.568 indicate that members with more friends tend to have a higher value of β_{0i}, which represents a higher level of intrinsic motivation to post reviews. This positive and significant is *consistent* with the notion that members derive social benefits from such contributions (e.g., Zhang and Zhu 2011). The statistically significant negative estimate in the second row (δ_{12} =-2.285) implies that the monetary reward was much less effective for members with more friends, compared to those with fewer friends. Together, these results show that without a monetary reward, members with more friends tend to contribute more than other members, *ceteris paribus*. However, when a monetary reward was introduced, members with more friends were influenced more negatively than the other members. This finding is consistent with the notion that reputation concerns may "crowd out" intrinsic motivations (Benabou and Tirole 2006, Ariely et al. 2009). These estimation results are qualitatively consistent with the model-free evidence and the main model, but are more precise quantitatively.

Results from the last two columns are related with the log-transformation of average logins, and the average number of orders. Except for one case, most of the estimates are statistically insignificant. These findings indicate that the level of other activities by a member does not have much power in explaining the differences among the β_i estimates across individuals, once the number of friends is controlled for. The last cell in the table shows that a member with a larger number of orders on this website reinforces the increasing trend of postings.

Finally, the estimation results related with endogeneity are reported in Table A3. The key result from this model is the parameter for the instrumental variable $\ln(Circles_i)$, which is positive and statistically significant (0.992), indicating that it is a strong instrument. The correlations between the endogenous equation and the other four equations are all statistically insignificant and almost 0, except for one with a value of 0.153. The lack of high correlations between equations (A4) and (A5) also indicates that endogneity is not a serious issue here.

<Place Tables A2 and A3 about here>

Appendix B. Examinations of Alternative Explanations and Review Quality

1. Alternative Explanations

This part provides more details on how we rule out a few alternative explanations to the moderating effect of the number of friends.

Change in the costs of posting reviews. Posting a review can involve non-trivial costs, and potential contributors weigh the costs against the value to decide whether or not to post a review (Avery et al. 1999; Hennig-Thurau et al. 2004). Thus, we examine several alternative explanations based on the possibility that the perceived cost of posting reviews might have changed because of the monetary rewards. In our context, such costs include the time spent logging into the community websites, the risk from product purchases, and the efforts of writing the review. We consider these extraneous factors sequentially.

Login frequency. First, the community member must log into the community's website to leave a review. Before the regime change, the correlation between the (member-level) average weekly login frequency and the average review contribution is positive (rho=0.39) and significant (p<0.001). Thus, we consider the alternative explanation that community members with more (fewer) social connections are less (more) likely to log into the website after the regime. We do not find support for this alternative explanation. In particular, community members with no friends decreased their login frequency after the regime change, while the login frequencies of most connected members are not significantly different after the regime change.

Order frequency. Intuitively, the amount of products ordered through the community may be positively correlated with review frequency. In fact, the correlation between (member-level) average orders and average review posting is moderately positive (rho = 0.12, p<0.001) before the regime change. This prompts us to consider the alternative explanation that socially connected members are less likely to order (and experience the products) after the regime change, compared with community members who are not socially connected. This alternative explanation does not find support from a before-after analysis of purchase orders. In particular, the order frequencies of the most connected members are not significantly different 4 weeks before or after the regime change.

2. Length of Reviews

The first measure for the effort put into a review is its length (operationalized as the number of Chinese characters *conditional* on writing a review). An examination of the review texts reveals substantial variation: while the shortest review has 10 characters, the longest one has over 1,000 characters. To accommodate the long tail of the data, we set up a conditional ln-regression model, where the number of characters in each review is assumed to follow a ln-Normal distribution:

$$\ln(y_{it}) = \alpha_{0t} + \alpha_{0i} + \alpha_{1i} Reward_t + \alpha_{2i} Tenure_{it} + \xi_{it}. \qquad \text{(A6)}$$

In this equation, y_{it} is the number of characters in a review posted by individual *i* in week *t*. The model specification is very similar to that of equation (A4). In addition, ξ_{it} is assumed to be *i.i.d* normal with a zero mean and a standard deviation to be estimated: $\xi_{it} \sim N(0, \sigma_\xi^2)$.

Comparing the results from this model with those in the HB model for the review contribution frequency (Table A2), we find that members with more friends not only tended to review more often, but also tended to write longer reviews ($\delta_{02} = 0.569$, with the 95% probability density region being (0.12, 1.02)). In addition, although they reduced their frequency of offering reviews after the monetary rewards were introduced (Table A2), the length of the reviews they wrote remained about the same ($\delta_{12} = -0.335$, not statistically significant, with the 95% probability density region being (-−0.88, 0.21)). In other words, the introduction of the monetary reward had a negative and significant impact only on the contribution frequency, but not on the lengths of the reviews once they decided to contribute.

3. Effort into Writing Reviews

The negative moderating effect of social connectedness is consistent with the prediction for social-image-conscious community members. Since perceptions of how monetary rewards affect social image are not directly measured, there is a need to rule out other alternative explanations. In particular, we examine whether the change in the review contribution decision is driven by the costs (efforts) of providing the review. To measure the effort put into each review conditional on writing a review, we conduct an additional text analysis based on the raw review texts of 1,500 product reviews contributed by members in the estimation sample from September 2009 to May 2010. Two research assistants, both native Chinese speakers and blind to research questions, independently rated the helpfulness of each review. To avoid fatigue effects in the rating process, all reviews were shuffled before being sent to the research assistants.

Efforts are measured on two seven-point Likert scales (1= "strongly disagree" to 7= "strongly agree"). The two statements are: "The reviewer put much thought into writing the review" and "The reviewer put much effort into writing the review." We also asked the research assistants to rate the perceived helpfulness. After rating the first 200 reviews, the two research assistants subsequently met to discuss their disagreements, some of which were resolved after their discussion. The final inter-coder reliability was measured using Cohen's kappa, which was 0.854, well above the desired level of 0.70 (Kolbe and Burnett 1991), suggesting strong consensus between the two raters. Thus, we proceeded to use the average of the two ratings, and we aggregated the ratings by regime (no rewards vs. rewards) and by social connectedness (with friends vs. with no friends).

We find that conditional on contributing a review, the amount of effort put forth by members without friends significantly decreased (M_{before} = 4.82, M_{after} =4.46, M_{diff} = 0.36 , p<.05). Similarly, the perceived helpfulness of the review (M_{before} = 5.39, M_{after} =4.92, M_{diff} = 0.47, p <.05). These results are interesting, but not quite surprising in retrospect. Recall that the focal community's policy is that monetary rewards are given to all contributed reviews, without stipulating any requirements for the contributed content. Such a policy may have likely induced a "transactional" mindset (e.g., Heyman and Ariely 2004) for the loners, who might have focused on getting a good deal for the transaction, that is, a low cost of effort per unit of reward.

In contrast, the monetary reward hardly affected the amount of effort put forth (M_{before} = 4.75, M_{after} = 4.79, M_{diff} =0.04, p>0.60) and the perceived helpfulness (M_{before} = 5.08, M_{after} =5.14, M_{diff} = 0.06, p >0.50) by the socially connected members. These results suggest that the "transaction mindset" effect seems to have had no significant impact on the socially connected, and their contributions continued to be driven by intrinsic motivations (e.g., helping others).

Combined with the results on the length of the reviews, we conclude that there is no support for the alternative explanation that members with friends decreased their contribution because of the higher level of effort. To summarize, we have identified and ruled out a number of alternative explanations. These findings lend greater internal validity to our main findings.

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TABLE A1
Testing the Violation of Exclusion Restrictions

Priors	Parameter Estimates			
	γ_1	γ_2	γ_3	γ_4
N(0,1)	-0.0531	-0.0516	-0.0331	-0.0046
	(-0.15,0.02)	(-0.11,0.01)	(-0.09,0.03)	(-0.03,0.03)
N(0,100)	0.8443	-0.9923	-0.0067	0.0245
	(-0.02,1.71)	(-2.09,0.09)	(-0.08,0.07)	(-0.06,0.11)

TABLE A2

Estimation Results for the Hierarchical Bayes (HB) Model

	Results for the top-level (choice) model	Results from the lower-level model $\Delta = \{\delta_{ab}\}$			
	Population mean	Intercept	ln(*Friends*)	ln(*AvgLogin*)	ln(*AvgBuy*)
Intercept (β_{0i})	−5.750 (−6.74,−5.04)[1]	-5.8968 (-6.95,-5.13)	1.568[2a] (0.94,2.25)	-0.242 (-0.75,0.28)	-0.299 (-0.73,0.05)
Post-reward dummy = 1 if monetary rewards are provided (β_{1i})	-0.579 (−1.36, 0.97)	-0.133 (-1.33,1.44)	-2.285[2b] (-3.08,-1.53)	0.456 (-0.12,1.02)	0.149 (-0.22,0.65)
Cumulative number of reviews a user wrote until the last week: CumReview (β_{2i})	-0.076 (-0.11,-0.05)	0.091 (0.05,0.13)	0.021 (-0.03,0.07)	0.026 (-0.01,0.07)	0.016 (-0.01,0.04)
Number of weeks as a user on this website: Tenure (β_{3i})	0.125 (0.09,0.16)	-0.065 (-0.12,-0.02)	-0.039 (-0.11,0.03)	-0.040 (-0.09,0.01)	0.021 (0.00,0.04)

Notes: [1] Parentheses are 95% probability density regions from the posterior distribution

[2a-2b] Interpretations of coefficients

[2a] Level of social connectedness has a positive and significant effect on the willingness to contribute in the voluntary regime.

[2b] Level of social connectedness has a positive and significant effect on the willingness to contribute in the voluntary regime.

TABLE A3

Results from the Endogenous equation in the lower-level HB model

	Intercept	ln(*Circles*)	ln(*AvgLogin*)	ln(*AvgBuy*)
Ln(Number of Friends)	0.176 (0.13,0.22)	0.992 (0.92,1.06)	-0.234 (-0.30,-0.17)	-0.001 (-0.02,0.02)

FIGURE A1

Histogram of Individual-Level Response to Monetary Rewards