Online Appendix
Motivation of User-Generated Content:
Social Connectedness Moderates the Effects of Monetary Rewards

Part 1. 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:

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

This decision is based on a latent-utility:

$$U_{it} = \beta_{0it} + \beta_{1i} PostReward_t + \beta_{2i} CumReviews_{it} + \beta_{3i} Tenure_{it} + \epsilon_{it} \tag{A2}$$

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:

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

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).

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

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

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

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)[1]; 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.

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

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) 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>

Part 2. Examinations of Alternative Explanations and Review Quality

2.1. 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.

2.2. 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:

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

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.

2.3. 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 ($M_{\text{before}} = 4.82$, $M_{\text{after}} = 4.46$, $M_{\text{diff}} = 0.36$, $p < .05$). Similarly, the perceived helpfulness of the review ($M_{\text{before}} = 5.39$, $M_{\text{after}} = 4.92$, $M_{\text{diff}} = 0.47$, $p < .05$). 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 ($M_{\text{before}} = 4.75$, $M_{\text{after}} = 4.79$, $M_{\text{diff}} = 0.04$, $p > 0.60$) and the perceived helpfulness ($M_{\text{before}} = 5.08$, $M_{\text{after}} = 5.14$, $M_{\text{diff}} =$

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 (-0.15,0.02)	-0.0516 (-0.11,0.01)	-0.0331 (-0.09,0.03)	-0.0046 (-0.03,0.03)
N(0,100)	0.8443 (-0.02,1.71)	-0.9923 (-2.09,0.09)	-0.0067 (-0.08,0.07)	0.0245 (-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