Peer Effects and the Production of Online Reviews: A Message Level Analysis

Research-in-Progress

Zhihong Ke
Carlson School of Management,
University of Minnesota
321 19th Ave S, Minneapolis, MN
55455
kexxx037@umn.edu

De Liu
Carlson School of Management,
University of Minnesota
321 19th Ave S, Minneapolis, MN
55455
deliu@umn.edu

Abstract

Online reviews are a dominant resource for consumers. Extant research on online review generation has primarily focused on the valence of online review, the volume of online review however remains largely unexamined. This study examines the peer effect on content production. Using a unique data set, we track and measure peer effect at message level. We find that peer effect does exist and it is attributed to the characteristics of the receiver, the object and the message, the relationship between the sender and the receiver. Intriguingly, our findings show that not all friends have the same effect on content production. A user is more likely affected by friends who share salient and relevant content and whom the user admires. Our findings hold implications for online review platform designer and marketers in terms of utilizing peer effect to facilitate content generation and spreading Word of Mouth.

Keywords: Peer effects, Online reviews, Content production, Word of Mouth
Introduction

Online reviews of products, services, and businesses have become a dominant source of information for consumers. A 2013 report by Dimensional Research concluded that approximately two-thirds of U.S consumers reported reading online reviews, among them, an overwhelming 88 percent said that their buying decisions were influenced by online reviews (Dimensional Research 2013). On the other hand, very few ordinary consumers write online reviews. Online review platforms have used many strategies to encourage users to submit reviews on products and services, including automatic reminders and providing financial incentives.1 One of the popular strategies, as practiced by leading online review platforms such as Yelp, is to let users of online review platforms connect with one another online and feed them with reviews written by their friends (which we call “friend-generated” reviews). Incidentally, platforms that rely on network of unpaid reviewers appear to be most successful in reviewer productivity and retention, etc. Indeed, Yelp credits its voluminous reviews to online communities they cultivate over the years. The conventional wisdom is that by having a community of users, they may respond to contribution made by their friends, and therefore end up writing more reviews. However, there has not been empirical evidence on whether this is the case.

Existing literature on peer effects in peer-to-peer file sharing suggest that the effects may not be straightforward. While some authors find that peer contribution lead to more contribution by focal users (Xia et al 2011), others find that peer contribution may lead to free-riding (Asvanund and Clay 2004). It is unclear which effects dominate, especially when peers are connected friends and the content reflects the identity of the contributor, such as in online product reviews.

Therefore, the goal of this study is to answer the following questions: what moderates the magnitude of the peer effects in the production of online reviews? Is it characteristics of the content, characteristics of the sender, the relationship between the sender and receiver, or characteristics of the product/service being reviewed? Answers to these questions are important for online review platforms and many other user-generated content sites. By understanding the moderators of peer effects in the production of online product reviews, we can help online review platforms develop better ways of filtering and presenting peer content to maximize the production of user-generated content.

We assemble a unique data set to address the above questions. Our data is collected from Yelp, the most popular online review site in US. We focus on content production (i.e. generation of new reviews) rather than content consumption, information diffusion, or adoption. Producing new content typically requires more time and effort than merely consuming and passing along it, although the latter are important online behaviors on their own. Writing a review for a store also involves one’s online social identity because reviews may convey information about the user’s views, tastes, and personalities, and contribute strongly to a user’s online identity. Despite the importance of user generated content to online platforms such as online review sites, its production is not yet adequately researched.

We focus on the relationship between a friend’s review and the user’s subsequent review of the same store. This is different from studies of peer effects via social network measures (e.g. centrality and structural holes), where the information flow is inferred but not directly measured. We study peer effects at a more granular message level. Such a “microscopic” lens provides a number of benefits: it allows us to more precisely measure the quantity and quality of information flow. Because we know exactly of timing of friend reviews and the follow up reviews, we can avoid some of the identification-related issues such as reverse causality. Our choice of a more granular level of analysis, together with our focus on the production of user generated content, enables us to make a unique contribution to the user-generated content literature.

The rest of our paper proceeds as follows. We next review several related literature streams, followed by the development of our main hypotheses. We then present our empirical models, research data, results and discussion. The last section concludes the paper.

1 For example, Epinions employs a revenue sharing strategy to elicit review production. Similarly, Amazon offers free products to those top reviewers in exchange for their reviews.
Related Literature

Empirical studies on the production of online review have so far mainly examined the valence of reviews (i.e., what rating to give). Prior literature suggests that the friends’ rating of a user affects what rating the user gives, which is moderated by product characteristics such as popularity, and by source friend characteristics such as experience (e.g., Wang, Zhang, & Hann, 2010; Lee, Tan, & Hosanagar, 2013). In addition, previous research has shown that the rating is affected by the rater characteristics such as rating frequency, expertise, and popularity (Moe & Schweidel, 2012; Goes, Lin, & Yeung, 2014), existing ratings (e.g., Sridhar & Srinivasan, 2012; Ma, Khansa, Deng, & Kim, 2013), and two types of biases: purchasing bias and self-selection bias (e.g., Hu, Zhang, & Pavlou, 2009; Li & Hitt, 2008).

Several studies examine the volume of online reviews (e.g., whether to write a review), with a focus on the distribution of reviews among businesses and products. It is shown that consumers favor writing reviews for products/stores that are less available, less successful, controversial, or have high existing volume of online reviews (e.g., Chrysanthos Dellarocas, Gao, & Narayan, 2010). The issue of how social networks affect review production is largely unexamined.

Our work is related to a long literature on motivations to contribute to online communities. One class of motivations includes others’ appreciation of contributed content, in the forms of attention, recognition, and reputation (e.g., Nam, Arbor, & Ackerman, 2009; Rui & Whinston, 2011). Another set of motivations involve the desire to help other consumers out of either altruistic or reciprocal motives (e.g., Steinberg 1987; Price, Feick, and Guskey 1995). Compared with newer online review communities, early systems often lack explicit social networking features. Nevertheless, many of the motivations for user contribution may still be useful in explaining review generation.

On the relationship between an individual’s contribution and the social stimuli, two contrasting effects have been observed: a reinforcement effect and a substitution effect. Xia, Huang, Duan, & Whinston (2011) show that peer-to-peer file sharers behave in reciprocal manner: the greater benefits they get from the network, the more likely they continue contributing (i.e., reinforcement effect). Asvanund and Clay (2004) also studied participant behaviors across multiple file sharing networks but they found evidence of free riding (i.e., substitution effect). But a major distinction between file sharing platforms and online review platforms is that the platform we focus on is engineer to facilitate explicit and meaningful social interactions whereas file sharing platforms are not. For example, the former does not support social features such as friends or compliments. Thus, the observed reinforcements and substitution effects may have different explanations on two kinds of systems.

Several studies start to look at the effect of friends on peer-to-peer lending (Liu, Brass, and Chen 2014), product adoption (Zhang, Liu, and Chen 2014), content diffusion (Susarla, Oh, and Tan 2012), types of generated photos (Zeng and Wei 2012), and rating (Wang, Zhang, and Hann 2010). We add to this stream of studies by focusing the peer effects on review production, which is arguably very central to user generated content platforms supported by social networking features.

Hypotheses

We are interested in what determines the probability of a user reviewing a store previously reviewed by a friend of the user. This problem setting is abstractly described as a sender-receiver system (see Figure 1), where a sender (friend) sends a message (the review) about an object (the store) to the receiver (the user) who may respond (write a follow up review) or not.

Based on the sender-receiver framework, we analyze the probability of a response as function of different elements of the framework and their relationships, including characteristics of the receiver, characteristics of the object and the message, characteristics of the sender, and the relationship between the sender and the receiver, and the relationship between the receiver and the object.

Several underlying reasons could potentially explain why a receiver is influenced by a sender’s message. One reason is that the message carries information that receiver finds relevant such that a receiver is more likely to follow up on it. We call this an “informational” influence. The receiver may also view the sender as a model to be imitated or an upholder of a social norm or identity. We call this a “normative” influence. Finally, the receiver may view the sender as a peer producer and as such, the receiver may differentiate from
the sender to avoid effort duplication or losing his/her own distinct identity. We call this a “competitive” influence. We will draw upon different influence concepts, sometimes multiple at the same time, when we develop hypotheses for the sender-receiver system.

We find the elaboration likelihood model (ELM) to be particularly helpful for theorizing the effects of peer reviews. The ELM is a framework for understanding how users react to a particular persuasion message. Prior ELM literature has identified several relevant factors that determine a message’s persuasiveness: product involvement, message involvement, and social involvement (e.g., Bhattacherjee & Sanford, 2006; Burnkrant & Unnava, 1995; Haugtvedt & Petty, 1992; Moore, Hauksnecht, & Thamodaran, 1986). Adapting these insights to the context of online reviews, we argue that the extent to which friend reviews influence attitude and behavior is jointly determined by the extent to which the store is relevant for the user (product involvement), the review is attractive for the user (message involvement), and the friend is socially related to the user (social involvement).

**Characteristics of the friend**

The ELM (Petty and Cacioppo 2012) is a dual-process theory of attitude formation and change, and argues that the effectiveness of persuasive communications is determined by the routes to persuasion: central or peripheral routes. The amount of cognitive energy the recipients of the persuasion message devote to the message varies, depending on what the message is, which in turn determines the attitude formation and change (Petty and Cacioppo 2012): the more energy devoted, the stronger effect on attitude formation and change.

Prior research on ELM has showed that source credibility such as expertise has positive impact on perceived usefulness of information (Bhattacherjee and Sanford 2006), and it affects persuasiveness via a peripheral route rather than a central route (Moore, Hauksnecht, and Thamodaran 1986), indicating source credibility has weak impact on the formation and change of attitude and behavior. In our context, an elite user’s reviews, as informational influence, are more authoritative and trustworthy than an entry-level user’s, thus the user likely devotes more energy to write a follow-up review. However, from the perspective of competitive influence, it is difficult to add value after an elite user has reviewed a store, which reduces the incentive to follow up. We hypothesize a positive overall effect but acknowledge a negative effect is also likely.

**Hypothesis 1:** A user is more likely to follow up on a review written by an elite friend than on a review written by a non-elite friend.

**Characteristics of the Review and the Store**

Prior ELM studies suggests that when the message is more relevant, it is more persuasive and has more impact on attitude and behavior (e.g., Burnkrant and Unnava 1995). Similarly, we argue that when the reviewed store is relevant to the focal user, the user is more likely persuaded, writes a follow-up review on
the same store. In other words, an attractive store is more relevant as consumers more likely visit it, thus reviews on it likely draw consumers’ attention. Moreover, consumers more likely write a follow-up review to benefit those people who share the same preference for stores.

The attractiveness of a store can be captured by two indicators, the average rating of the stores and the velocity of new reviews on the store. We expect that stores with a higher average rating are more likely visited by a user and thus more likely reviewed. Similarly, we expect that the past velocity of reviews on the store predicts the likelihood of a follow-up review.

The attributes of the review may have additional effects. Prior ELM research established that argument quality is positively associated with perceived usefulness of information (e.g., Bhattacherjee & Sanford, 2006). Accordingly, we argue that a more informative, appealing, or higher quality review, as reflected by the length of the review and the number of votes it garners the review, is more persuasive. We also expect that a positive rating on the review increases the receiver interests, thus may also increase the probability of a follow-up.

**Hypothesis 2a-b**: A user’s probability of following up on a friend review increases with the store’s (a) average rating and (b) velocity of new reviews.

**Hypothesis 3a-c**: A user’s probability of following up on a friend review increases with (a) the review’s length, (b) number of votes, and (c) rating.

**Characteristics of the User**

Users of online review platforms have different traits and states that dictate their level of contribution. In this research we focus on the latter as we shall control for a user’s time-invariant traits (e.g., gender and income). One import user state is her tenure on the platform. By incorporating tenure, we can capture the general trend of a user’s activity level. As a user’s tenure increases, the novelty of the platform dissipates and the user less likely gets involved in it. Thus, we expect a declining trend in a user’s activity level, as on many other online platforms (e.g., Goes et al., 2014).

**Hypothesis 4**: A user’s probability of following up on a friend review decreases with her tenure.

**The Relationship between the User and the Friend**

Prior ELM studies suggest that when people relate the information to themselves and to their own experience, the elaboration on information is greater and in turn, the formation and change of attitude and behavior are likely (e.g., Burnkrant and Unnava 1995). People likely relate the information conveyed by social important others such as role models and peers, thus are affected by them as they are likely driven to involve in social interaction with them such as reviewing on same store and discussing it.

In our context, when a user sees a friend review, her reaction is not only affected by the information content conveyed by the review, but also affected by her relationship with the friend. As we have noted, a friend review may have informational, normative, or competitive influence. Each of these influences have different implications for the probability of a follow-up review. A friend is more likely an information source, if the friend’s interests strongly overlap with the users. A review from such a friend is more likely seen by the user as personally relevant, and thus more likely followed up by the user. When a user frequently compliments a friend, the friend is more likely a role model and social norm source. A user trusts and imitates her role model. When a role model reviews a store, the user is likely to visit the same store and write a follow-up review. A friend and a user are more likely members of the same social group when they have many common friends. Past research suggests that online content producers are partly driven by a desire to establish an online social identity via perceived membership with a social group (Dellarocas, Gao et al. 2010). A strong identification with each other strengthens the reciprocity. A user is more likely to reciprocate a member of her social group (Xia, Huang et al. 2007) and to follow the social group’s norm on reviewing. On the other hand, from a producer’s perspective, having more common friends means overlapping audience. Past research has shown that people tend to share content that makes them look intelligent and unique (Ludford et al. 2004; Beenen et al. 2004). When two users share many common friends, they may avoid reviewing the same store to maintain their distinct online identities. On balance, we expect the user to more likely follow up with a friend review when they have many common friends, but acknowledge the opposite effect is also likely.
ELM literature has showed that more messages lead to higher likelihood of persuasion (e.g., Haugtvedt & Petty, 1992). As a content consumer, when a store has been repeatedly recommended and exposed to a user via friend reviews, she is likely to check the store out. As a content producer, the user may either be encouraged to chat about the same store driven by message involving, or be discouraged to iterate the same store out of the duplication information concern as few value is added by doing so and it does not help with identity building. A user’s friend network likely functions as an information pool where the user not only pulls relevant information from but also shares her own information with people who she has overlapping interests. As such, content producers likely favor message involving over redundant information concern. We therefore hypothesize that a user’s prior exposure to friend reviews of the same store has a positive effect, with a fair assumption that the more visits due to repeated exposure, the more content producers.

Certain peers may be more likely viewed as competition source and peer producers than close or inspirational friends. A local friend is such a case because a local friend is someone who has similar (location-based) knowledge and audience, but need not be a close friend or a role model. When a local friend writes a review, the user may view a follow-up review as redundant and not helpful for maintaining her unique online identity.

**Hypothesis 5a-d:** A user’s probability of following up on a friend review increases with (a) the preference similarity between the user and the friend, (b) the number of common friends, (c) the number of compliments from the user to the friend, (d) the user’s prior exposure to the same store via friend reviews, and (e) decreases if the user and the friend are collocated.

**Data and Empirical Model**

We collect data from one of the largest online review sites in the world. The site is operated as a platform for unsolicited reviews for local businesses such as restaurants and schools. As of 2014, the site has over 100 million visitors each month and over 50 million reviews. One of the prominent features of the site is its social networking functions. Users can befriend, follow, and send compliments to one another. They may also vote on any review (e.g. a helpful or funny vote). Friend reviews are prominently featured on the user’s homepage and in the user’s personalized search results. Each year, the site selects elite reviewers based on the quality and quantity of last year’s reviews, and the selected users are honored with an elite badge. Besides online social networking, the most active reviewers often organize offline events such as parties and store visits, with the help of local community organizers (who are themselves volunteers).

We focus our data collection on restaurant reviews in the state of Washington (WA). We start with the 551 elite users located in Seattle, WA. We scan the friend list of each elite user, which results in 33,815 friends. From these friends, we include those who are (a) based in Washington and (b) have written at least one review for WA restaurants in the past year in our data set. This results in about 6,016 users and these users have 8,029 friends who have written at least one review for WA restaurants in the past year. For each user in the dataset, we scan the user’s profile (including stats) and friend list every month between March 2013 and April 2014. We also collect all of their reviews and incoming compliments since March 2012. We choose the period between April 1, 2013 and November 10, 2013 as our study period to minimize truncation. We separately collect reviews on all 10,608 WA restaurant stores in our dataset, which results in a total of 352,826 reviews.

For the purpose of our analysis, we cross users with reviews of their friends for WA restaurants during the study period, excluding all users who have closed their accounts in the study period. We then compute our dependent variable followup. If the user has subsequently written a review for the same store of the friend review, we let followup=1, otherwise followup=0. Variable definitions, their measurements, descriptive statistics are described in Table 1.

Because our dependent variable is binary, we adopt a conditional logit (also called fixed-effects logit) model. In this model, the probability of following up on a friend review is conditioned on the total number of follow-ups by the same user such that the effect of time-invariant individual characteristics (e.g. gender and elite status) is canceled out. This feature allows us to control for unobservable individual heterogeneities. Specifically, we assume the utility for user \(i\) to follow up a friend review \(k\) is a function of a constant user-specific term \(\alpha_i\), dynamic user characteristics \(X_i\), friend characteristics \(Y_k\), review characteristics \(M_k\), and store characteristics \(N_k\), characteristics of the relationship between the friend and the user \(O_{ik}\), additional controls, and a random disturbance term \(\varepsilon_{ik}\).
Peer Effects and the Online of Online Reviews

\[ U_{ik} = \alpha + \beta_1 X_k + \beta_2 Y_k + \beta_3 M_k + \beta_4 N_k + \beta_5 O_{ik} + \beta_7 \text{Control}_S + \epsilon_{ik} \]  

By assuming all \( \epsilon_{ik} \) of the same user are i.i.d. type I extreme values, the conditional probability of user \( i \) follows up on the friend review \( k \), given she follows up on \( n_i \) friend reviews, is

\[ \text{Prob}(\text{followup}_{ik} = 1 | n_i) = \exp(U_{ik}) / \sum_{n_i} \exp(U_{ik}) \]  

Substituting (1) into (2), we can see that the term \( \alpha \) is cancelled out. Using (2), we write the log-likelihood function for all observations and use it to derive the parameter estimates.

Results

We would like to first get a sense of how frequently a user follows up a friend review with her own. We find that about 0.62% friend reviews are followed up by a user’s own review, resulting in 3,567 reviews by 9,766 users in about 7 months. To make sense of these rates, we may compare them with the rate of a consumer responding to search engine ads. Assuming a click-through rate of 3% and a conversion rate of 3%, one ends up having 0.09% of instances that a consumer follows up with a purchase, sign-up, or call. Granted, some of the follow-up reviews may be due to other influences unobservable to us, but even when we restrict the response window to 60 days, the rate of response is still at 0.22%. Another way to look at it is to calculate the ratio of follow-up reviews to the total number of reviews written by the same users in the study period.

We have 1,253 follow-up reviews (assuming 60 day window) and 15,597 total reviews written by the same users within roughly the same period. This puts the follow-up reviews at roughly 8% of all reviews. These numbers tentatively suggest that friend reviews could be a salient source of influence in the generation of online reviews.

To test our hypotheses, we construct a sample of followup decisions that consist of users and their friends’ reviews. 571,493 instances of friend reviews for 4,459 users are generated. After deleting instances with missing data (missing gender information), we end up with 542,559 data points. Each user faces an average of 128 follow-up decisions.

The conditional logit regression results are presented in Table 1 with followup as the dependent variable. Some independent variables (e.g., log_compl_tofr and log_photos) are log transformed because of their skewed values. No multicollinearity is found among independent variables. Table 1 shows that fr_elite has no significant impact, so H1 is not supported. This suggests that the concern of value-adding may cancel out the effect of an authoritative information source. ave_rating and log_store_rev_speed are positively related with followup, indicating H2a-b are supported. Thus, as we expected, friend reviews of attractive stores are more likely followed up, supporting the informational sourcing view of peer effects. H3a-c are supported: log_votes, rating, and review_len have a positive impact on followup. A user’s tenure is negatively associated with followup. Thus H4 is supported, suggesting that the longer a user is with the platform, the less likely she follows up on friend reviews. H5a is strongly supported, indicating that reviews from friends with similar preference for store popularity (fr_sim_storepref) is more likely to be followed. fr_sim_comfriends has no impact on followup, suggesting H5b is not supported. This may suggest that a positive effect of behavioral modeling among close social groups is canceled out by a negative effect of content duplication concerns. compl_tofr is positively related with followup, thus H5c is supported. This indicates that a user likely follows the reviews written by friends who she admires and models. The effect of store_exposure on followup is positive (odds ratio=1.077). Thus H5d is supported, suggesting that repeated exposure to friend reviews of the same store results in a higher probability of following up. In other words, friend reviews have cumulative effects on the user. Interestingly, collocation (fr_local) has a negative impact on followup, thus H5e is supported. A user likely views a collocated friend as peer producers. Iterating the same store of a local friend review results in content duplication and undermines a user’s online identity building.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
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<tbody>
<tr>
<td>Mean</td>
<td>Std. Dev.</td>
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<td>Odds Ratio (se)</td>
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<th>Regression Results</th>
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<th>Std. Dev.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>followup</td>
<td>Whether same store review has been written (write 1; otherwise 0)</td>
<td>0.01</td>
<td>0.07</td>
<td>-</td>
</tr>
<tr>
<td>fr_elite</td>
<td>Whether friend is elite users (elite 1; otherwise 0)</td>
<td>0.43</td>
<td>0.49</td>
<td>0.945 (0.044)</td>
</tr>
<tr>
<td>fr_female</td>
<td>Whether friend is female (female 1; otherwise 0)</td>
<td>0.72</td>
<td>0.45</td>
<td>0.917+ (0.046)</td>
</tr>
<tr>
<td>ave_rating</td>
<td>Average rating of the store</td>
<td>3.81</td>
<td>0.5</td>
<td>1.232*** (0.060)</td>
</tr>
<tr>
<td>store_rev_speed</td>
<td>Velocity of the store’s new reviews (the number of existing reviews divided by the store age)</td>
<td>0.19</td>
<td>0.29</td>
<td>11.769*** (0.989)</td>
</tr>
<tr>
<td>store_age</td>
<td>The number of years has elapsed since the store was set up on the site.</td>
<td>1,156.58</td>
<td>889.55</td>
<td>1.000 (0.000)</td>
</tr>
<tr>
<td>review_len</td>
<td>The review length</td>
<td>986.88</td>
<td>646.45</td>
<td>1.000* (0.000)</td>
</tr>
<tr>
<td>votes</td>
<td>The number of votes the review received</td>
<td>4.17</td>
<td>9.93</td>
<td>1.063* (0.026)</td>
</tr>
<tr>
<td>rating</td>
<td>The rating of friend review</td>
<td>3.82</td>
<td>1</td>
<td>1.055* (0.025)</td>
</tr>
<tr>
<td>tenure</td>
<td>The number of days has elapsed since the focal user on the site</td>
<td>1,423.02</td>
<td>626.51</td>
<td>0.997*** (0.001)</td>
</tr>
<tr>
<td>fr_sim_storepref</td>
<td>The similarity of preference for store popularity between the focal user and friend</td>
<td>0.83</td>
<td>0.19</td>
<td>8.726*** (2.398)</td>
</tr>
<tr>
<td>fr_sim_comfriends</td>
<td>The number of common friends the focal user and friend share.</td>
<td>22.16</td>
<td>35.51</td>
<td>1.001 (0.000)</td>
</tr>
<tr>
<td>compl_to_fr</td>
<td>The number of compliments sent to friend by the focal user.</td>
<td>0.5</td>
<td>3.02</td>
<td>1.201*** (0.040)</td>
</tr>
<tr>
<td>store_exposure</td>
<td>The number of times the focal user previously saw the store via friends' reviews</td>
<td>0.11</td>
<td>0.53</td>
<td>1.077*** (0.018)</td>
</tr>
<tr>
<td>fr_local</td>
<td>Whether friends and the focal user are collocated (collocate: 1; otherwise 0)</td>
<td>0.97</td>
<td>0.17</td>
<td>0.774* (0.079)</td>
</tr>
<tr>
<td>compl_sent</td>
<td>The number of compliments sent by the focal user in last 2 weeks</td>
<td>25.34</td>
<td>39.78</td>
<td>0.914*** (0.015)</td>
</tr>
<tr>
<td>compl_rec</td>
<td>The number of compliments received by the focal user in last 2 weeks</td>
<td>4.9</td>
<td>16.49</td>
<td>0.973 (0.023)</td>
</tr>
<tr>
<td>no_frs</td>
<td>The aggregate number of friends the focal user has</td>
<td>223.91</td>
<td>601.17</td>
<td>0.463*** (0.096)</td>
</tr>
<tr>
<td>past_fr_reviews_p</td>
<td>The number of friend reviews for WA restaurants in last 2 weeks divided by the number WA friends.</td>
<td>0.57</td>
<td>0.67</td>
<td>1.028 (0.139)</td>
</tr>
</tbody>
</table>

Log-likelihood: -11,154.85
Adjusted R-squared: 0.073
N: 206,749

Note for Regression Results: The values in parentheses are standard errors. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

### Discussions

This study seeks to extend understanding of peer effects in review production. The results of this study show that consumers’ response to friend reviews varies, depending on the information conveyed by friend...
reviews. Their follow-up decisions on review writing is a function of the characteristics of the store, the review and the user, and the relationship between the user and her/his friends.

Our research makes several contributions. First, we contribute to the issue of content generation, which so far received only a small portion of attention in the user-generated content literature. One important takeaway from our analysis and findings is that what motivates a user to consume certain content tends to discourage the user to produce related content. This highlights the challenge in studying content production and underscores the importance of unpacking the multiple mechanisms underlying content consumption-production processes. Second, we contribute to the peer effect literature by examining it at the message level. Our study tracks actual information flow between social actors rather than using proxies of social influence such as social network characteristics. Our approach offers several advantages in isolating different moderators of peer effects and is applicable to other studies of peer effects using fine-grained data.

Our results hold interesting implications for platform designers and marketers. From a platform design perspective, our study provides evidence of the peer effect, that is, content produced by socially connected peers can indeed facilitate production of new content. Our findings highlight that the peer effect is a double-edged sword with both encouraging and discouraging effects. Several salient moderators identified in this study can be used to filter peer content shown to the users so as to maximize their content generation potential. From a marketing perspective, our findings suggest that inducing word-of-mouth among peer consumers can be viable and important, but not all peer content has equal strength in inducing word-of-mouth. For example, presenting friend reviews on attractive stores, high-quality friend reviews, reviews written by similar others, role models, and repetitive reviews on the same store increase review production and word of mouth, whereas reviews written by co-located friends should be filtered out and not present as they discourage review production and word of mouth.

Conclusions

This study examines an important question about peer effect in the production of online reviews: when do users follow up on reviews produced by friends? Answers to this question hold important implications for online review platforms in terms of selecting peer content to present to its users. To our knowledge, this is the first study to empirically examine such a question. Using a unique data set, we track whether a user follows up on a friend review. We find that peer effect does exist and it is attributed to the characteristics of the receiver, the object and the message, the relationship between the sender and the receiver. The act of following up a friend review with one’s own is costly both in time and effort and in terms of losing uniqueness. Intriguingly, our findings show that not all friends are the same in inducing follow-ups. A user is more likely to follow up on friends who share salient and relevant content and whom the user admires. When these qualities are absent, a user might be driven to avoid following up on their friends.

As any study of user responses in complex social and informational environments, our study faces the challenge of attributing an outcome to multiple sources of influence. We cannot perfectly attribute new reviews to a prior peer review, although we have taken a few features to reduce attribution errors. We choose to focus on friend reviews as a social stimuli because friend reviews are a salient section on any user’s homepage. We limit ourselves to follow up reviews of the same store, so that we filter out many other sources of influence that may lead to new reviews but not necessarily on this store. Finally, we use moderator variables specific to the friend review as a way of increasing our confidence that a subsequent review could indeed be attributed to the friend review. That said, as a work-in-progress, our study has several limitations that require drastic improvements. We only analyze the quantity of follow-up reviews, it would be useful to incorporate review quality to gain more insights on the peer effects. Although it would be ideal to compare friend reviews with stranger reviews, the limitation of our dataset prevents us from reliably identifying reviews forwarded by strangers. We do not yet have evidence of casual effects and this should be a goal for our next step. Finally, we have not taken advantage of the rich content of the review texts. We believe that we can gainfully leverage such a useful source of unstructured data.
References


