Do Online Friends Bring Out the Best in Us?

The Effect of Friend Contributions on Online Review Provision

Zhihong Ke

zke@clemson.edu

Clemson University

De Liu

deliu@umn.edu

University of Minnesota

Daniel J. Brass

daniel.brass@uky.edu

University of Kentucky

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Abstract

User-generated online reviews are crucial for consumer decision-making, but suffer from under-provision, quality degradation, and imbalances across products. This research investigates whether "friend contributions cues," in the form of highlighted reviews written by online friends, can motivate users to write more and higher-quality reviews. Noting the public-good nature of online reviews, we draw upon theories of pure altruism and competitive altruism to understand the effects of friend-contribution cues on review provision. We test our hypotheses using data from Yelp, and find positive effects of friend contribution cues. Users are three times more likely to provide a review after a recent friend review than after a recent stranger review, and this effect cannot be solely explained by homophily. Furthermore, reviews written after a friend's review tend to be of higher quality, longer, and more novel. In addition, friend reviews tend to have a stronger effect on less-experienced users and less-reviewed products/services, suggesting friend-contribution cues can help mitigate the scarcity of contributions on "long-tail" products and from infrequent contributors. Our findings hold important implications for research and practice in the private provision of online reviews.

Keywords: Online reviews, online friends, public goods, competitive altruism, contribution quality

1. Introduction

User-generated online reviews have become a dominant source of information for consumers. According to a 2018 report by BrightLocal, 85 percent of consumers said that their buying decisions were influenced by online reviews (BrightLocal 2018). Prior research consistently shows that increasing the volume of online reviews has a positive influence on product sales (e.g., Dellarocas et al. 2007; Duan et al. 2008; Forman et al. 2008). Therefore, it is of practical importance for vendors and online review platforms (ORPs) to attract many user-generated reviews.

In reality, however, online reviews are under-provisioned (Fortune 2016; Goes et al. 2016). Studies estimate that only 1 percent of consumers have ever written an online review (Anderson and Simester 2014; Yelp 2011). This is not entirely surprising because online reviews are privately-provisioned public goods; consumers have strong incentives to free-ride on the contributions of others, leading to under-provision. The contribution to online reviews is also highly imbalanced across products (Burtch et al. 2018; Dellarocas et al. 2010; Tucker and Zhang 2007). For example, only 2.2 percent of restaurants on Yelp receive more than 13 reviews per month, whereas more than 30 percent receive no review (Luca 2016). Adding to these concerns is a rapid decline in quality: the average length of online reviews has decreased from 600 characters in 2010 to just over 200 characters in 2017 (Liu et al. 2007; Mudambi and Schuff 2010; ReviewTrackers 2018). To address these issues, ORPs have used several approaches, including offering coupons, discounts, and other financial incentives to motivate review contributions.[1] Recent research suggests that such tangible rewards are effective, but often have downsides such as resulting lower quality reviews and eroding consumer trust (Burtch et al. 2018; Ghasemkhani et al. 2016; ReviewMeta.com 2016; Stephen et al. 2012).

Our research explores a new "friend-contribution-cue" approach – i.e., motivating review contributions by highlighting reviews written by one's online friends. The friend-contribution-cue approach is applicable

[1] For example, Epinions employed a revenue-sharing strategy with reviewers to encourage review generation. Amazon once offered free products to top reviewers and allowed product owners to offer free or discounted products to reviewers in exchange for their reviews, but discontinued this practice under criticism.

when ORPs support social networking among users.[2] Such ORPs can highlight the contributions of a user's online friends. For example, Yelp shows friend reviews on top of other reviews on business pages and users' homepages. Highlighting friend reviews may aid users in their discovery of new products and services, but its effects on users' contribution behavior are unexplored. We ask the following questions in this research:

- Can friend-contribution cues motivate a user to contribute a new review?
- Can friend-contribution cues lead to higher quality reviews?

Readers familiar with the social influence literature may assume that friend contributions increase users' own contributions. Prior research has found that friends generate a positive social influence in private-goods domains such as the adoption of paid music and store check-ins (Bapna and Umyarov 2015; Liu et al. 2015; Qiu et al. 2018; Zhang et al. 2015). However, the public-goods nature of online reviews suggests a countervailing free-riding effect may exist: One user's contribution may substitute for another's, especially between online friends who are likely to hold similar opinions (Lee et al. 2016; Underwood and Findlay 2004). This free-riding effect has been noted in other public-goods contexts in the forms of social loafing, "volunteer's dilemma," and "bystander" effects (Darley and Latané 1968; Diekmann 1985; Karau and Williams 1993). Because of free-riding, it is unclear whether friend contributions lead to more or fewer reviews, especially considering that review writing is time-consuming and requires certain expertise. In addition, we do not yet know the effect of friend contributions on contribution quality or the distribution of reviews across products and users.

The friend-contribution-cue approach, if proven effective, can complement existing research studying social influences in online review writing behavior. Our approach differs from an alternative social-cue approach highlighting aggregate contributions (e.g., "3,786 users have recently contributed online reviews") (Burtch et al. 2018). Such aggregate-contribution cues fail to induce more reviews, although they may increase review lengths (Burtch et al. 2018). The friend-contribution cue operates very differently from

[2] Throughout the paper, we define a user as a registered member of an ORP because only registered members are allowed to make online friends and post reviews.

the aggregate-contribution cue. The former uses specific contributions by online friends, whereas the latter uses aggregate contributions by anonymous peers. As a result, friend-contribution cues are more personally relevant and targeted. Notwithstanding these differences, the two forms of social cues can be used together. We further differentiate our study from research on how ratings of friends affect subsequent ratings. Wang et al. (2018) focuses on whether one's friends' average ratings influences the focal users' ratings (provided that the focal users also provide ratings). It does not address a user's likelihood of offering a review or the quality of the review, as we do in our research.

We extend theories of public goods to understand the effects of friend-contribution cues on the quantity and quality of online review provision. One theory, called "*pure altruism*," holds that users contribute because they value the welfare of others; it implies that a friend's contribution would substitute for a focal user's contribution because of diminishing marginal benefits of an additional contribution to the public. Another theory, called "*competitive altruism*," holds that users make altruistic contributions to gain status in a community; thus, a friend's contribution could stimulate further contribution by signaling a relevance of contribution and a favorable audience for such contributions. Building on these countervailing arguments, we develop hypotheses about the effects of friend-contribution cues on one's own contribution in terms of both quantity and quality.

We test our hypotheses using a unique dataset of restaurant reviews from Yelp. Yelp provides extensive social networking features among users and highlights friends' reviews on business pages and users' homepages. In addition, Yelp lets users vote on each other's reviews and nominate outstanding users to become "elites", who enjoy many perks such as free dinner parties and tasting events. We assemble a user-restaurant-week panel of review contributions from 2,923 users toward 8,289 restaurants in the state of Washington over a period of 36 weeks. Using this panel, we formulate a discrete hazard model of a user's likelihood of reviewing a restaurant in a given week as a function of the number of friend reviews for the restaurant in the preceding week. We use this model to examine the effect of friend-contribution cues and how it varies with restaurant and user characteristics. We also study the effect of friend-contribution cues on review quality, which we measure using the number of *votes* received by the review, independent quality ratings by Amazon Mechanical Turk workers (henceforth *Turker Ratings*), and a review *novelty score* based on the review's content.

One of the challenges in estimating the effect of friend-contribution cues is the potential confound of the homophily effect; that is, two friends write reviews on the same restaurant because they have similar preferences. We control for the homophily effect using a user's future friends: future friends have similar preferences as the user, but their reviews may not influence the user's contribution decisions. Therefore, the effect of future-friends' reviews, which is driven by homophily alone, can be used as a proxy for the homophily effect.

2. Related Literature

In the following, we discuss the relation of this research to two literature streams – provision of online reviews and voluntary provision of public goods – with a focus on the role of social influence in each case.

2.1. Provision of Online Reviews

The online review literature has approached the provision of online reviews from three perspectives: valence, volume, and quality. A review's valence refers to the tone of the review as typically measured by the associated numeric rating. Research in this stream reveals that social factors including peer ratings (Lee et al. 2015; Ma et al. 2013; Sridhar and Srinivasan 2012) and friend ratings (Lee et al. 2015; Wang et al. 2018) may impact review valence. Lee et al. (2015) demonstrate that higher peer ratings induce users to also provide high ratings. Wang et al. (2018) study the effect of friend ratings on the valence of book reviews and find that users tend to give similar ratings as their friends. As a result, they suggest that ratings following after friends' ratings are more biased. Studies of review valence focus on whether a review leans positive or negative rather than on the likelihood of contribution and contribution quality.

Research on the volume of online reviews shows that characteristics of the product (Dellarocas et al. 2010), a user's consumption experience (Dellarocas and Narayan 2006), and reviewer characteristics (Goes et al. 2014; Moe and Schweidel 2012) can all affect the quantity (or likelihood) of review provision. Within this stream, a few studies examine how ORPs can increase the volume of online reviews using financial or social incentives. Burtch et al. (2018) show that financial incentives increase review volume but not length.

Financial incentives often lead to undesirable side effects such as lower quality reviews and eroding consumer trust (Burtch et al. 2018; Ghasemkhani et al. 2016; Stephen et al. 2012).

Burtch et al. (2018) and Chen et al. (2010) study the effect of social cues on the volume of reviews. Chen et al. (2010) demonstrate that, after being shown the median number of rating contributions, users below (above) the median increase (decrease) their contributions. Burtch et al. (2018) show that aggregate contribution cues increase review length but not volume. However, when combining financial incentives with aggregate-contribution cues, one could increase both review length and the volume of reviews. As noted in the introduction, the aggregate- and friend-contribution cues operate quite differently and thus may be used independently.

The literature on review quality concentrates on the association between textual features of reviews and the number of "helpfulness" votes it receives, an often-used proxy for review quality (Ghose and Ipeirotis 2011; Mudambi and Schuff 2010; Yin et al. 2014). This stream also examines the relationship between contextual factors, including product type and reviewer characteristics, and review quality (Lu et al. 2010; Mudambi and Schuff 2010). It, however, does not focus on the issue of how to promote review quality, with the exception of Burtch et al. (2018) who examines the effects of financial incentives and aggregate-contribution cues on review length, a correlate of review quality.

2.2. Social Influence and the Voluntary Provision of Public Goods

Prior research finds evidence of social influence among friends in many private-goods domains, including adoption of paid music services and products (Bapna and Umyarov 2015; Zhang et al. 2015), music consumption (Dewan et al. 2017), store check-ins (Qiu et al. 2018), and peer-to-peer lending (Liu et al. 2015).[3] As mentioned earlier, social influence in the private provision of public goods is different because of the free-riding tendency. In what follows, we focus on social influence in public-goods domains.

[3] In addition, the social network literature has many examples of friend performance positively affecting an individual's performance (e.g., in school and workplace settings) (Altermatt and Pomerantz 2005; Cook et al. 2007). Again, free-riding does not typically arise in these settings and some of the underlying mechanisms such as observational learning (e.g., modeling high levels of participation in teacher–student interactions) and social support (e.g., receiving help and guidance on homework assignments) may not apply to our context.

One stream of research investigates the effect of peer contributions in "electronic communities of practice," such as online discussion forums, Q&A forums, and knowledge-sharing communities (Wasko et al. 2009; Wasko and Faraj 2005). Contributions to these forums have characteristics of public goods, but they tend to disproportionately benefit people involved in a conversation (e.g., information seekers). Because of the directed nature of such contributions, researchers have relied on reciprocity theories to explain the effect of peer contributions (Jabr et al. 2014; Xia et al. 2011). The reciprocity theories may not apply in online reviews because online reviews benefit a broad audience rather than specific individuals.

Perhaps more relevant to this research is the literature on charitable contributions, which are a form of private provision of public goods. This stream widely acknowledges that peer contributions can potentially crowd out one's own contributions. For example, Tsvetkova and Macy (2014) show that observing others' helping behavior decreases one's own helping. However, findings are mixed on whether there is a positive or negative relationship between the contributions of others and one's own contribution (Shang and Croson 2009). To account for the positive relationships, this literature offers several informal explanations, including conformity (Bernheim 1994), achieving social acclaim (Vesterlund 2006), gaining social approval, and peer contribution as a signal of a charity's quality (Vesterlund 2003). The charitable giving literature has not examined the role of (online) friend contributions. Furthermore, online reviews are distinct from charitable giving in at least two dimensions: online reviews may reflect one's intelligence and skills, and there are user communities for online reviews.

3. Theoretical Background and Hypotheses

In this section, we develop the hypotheses for the effect of friend contribution cues (or *friend contributions* for short, provided that they are highlighted). Using restaurant reviews as an example, we examine how the addition of a friend review, *relative to that of a stranger review*, affects a focal user's contribution in terms of probability of contribution and review quality. We will focus on friends' recent contributions because we expect a decay effect (that we later confirm): the chance of a user acting on a friend's review while it is fresh is much higher than when the friend review has been posted for a long time. We note that it is common for studies of online reviews to focus on recent stimuli (Dellarocas et al. 2010;

Duan et al. 2008; Wang et al. 2018). We also limit ourselves to contributions to the same restaurant because we do not have a good way of attributing other-restaurant contributions to the focal friend reviews.

3.1. Effect of Friend Contributions on Review Quantity

To understand users' contribution behavior under the influence of friend contributions, we draw upon theories of private provision of public goods. Though social influence theories such as social learning and normative social influence may seem relevant (Aral and Walker 2011; Iyengar et al. 2011), we choose theories of public goods as an overarching theoretical framework for two main reasons.[4] First, social-influence theories are useful for explaining social contagion in the diffusion of products, services, and ideas, but they do not provide an explanation of why an individual contributes to public goods in the first place. Thus, they are incomplete for explaining contributions to public goods. Zeng and Wei (2013) made a similar observation when studying how social ties affect similarities of photos uploaded to Flickr. Second, most social influence theories do not address contribution quality, which is not an issue in adoption settings but is one of the important goals of this research.

We first draw upon a well-known theory of *pure altruism*, which suggests that individuals make altruistic contributions because they value not only their own welfare but that of others (Andreoni 1989, 1990). This theory is consistent with the idea that one of the main motivations for writing an online review is to help others make a better purchase decision (Dichter 1966; Hennig-Thurau et al. 2004). There is also neural evidence in support of pure altruism – peoples' neural activity in value/reward areas correlates with their rate of actual charitable donations (Harbaugh et al. 2007; Hubbard et al. 2016).

The theory of pure altruism leads to an important consequence for peer contributions (Tsvetkova and Macy 2014): As peers contribute more to public goods, an additional unit of contribution adds less value to the collective good and, therefore, an individual has less incentive to contribute. Such a *substitution effect* has been documented in contexts such as charitable contribution (Shang and Croson 2009; Tsvetkova and

[4] Social influence and theories of public goods do interact, especially in the case of competitive altruism theory. Later, when deriving implications of competitive altruism for the effect of friend contributions, we do invoke arguments similar to social influence theories: e.g., we argue that friend contributions signal relevance (similar to the arguments of social learning) and social desirability of such contributions (similar to the arguments of normative social influence), though we place such arguments in the framework of competitive altruism.

Macy 2014; Witty et al. 2013). The substitution effect can be further amplified when the peer contribution is a friend contribution. This is because online friendships tend to form around shared interests and opinions (Dey 1997; Moretti 2011). When a user sees a friend review on a restaurant, compared to a stranger review, the user is more likely to consider writing her own review as redundant. Therefore, she is less likely to offer a review of the same restaurant. In sum, the pure altruism theory of public goods would suggest that a friend review, relative to the stranger review, would reduce a user's own contribution.

Another theory of public goods, called *competitive altruism*, holds that people contribute to public goods not because of their genuine concern for others, but to gain status in a social group that rewards individuals based on their relative contribution and commitment to the group (Hardy and Van Vugt 2006; Roberts 1998; Willer 2009).[5] Recognizing that individuals may lack the motivation to contribute to public goods, the group as a whole has the incentive to collectively reward people who make outstanding altruistic contributions (e.g., by granting such individuals prestige, trust, and preferential treatment in partner selection). One such example is the peer review of journal submissions: Academic communities use best-reviewer awards, recognition by journal editors, and promotion to editorial positions to motivate voluntary peer reviews. Competitive altruism holds that in a community that associates status rewards with outstanding altruistic behaviors, individuals would compete to make altruistic contributions in ways that suggest a high level of competence, generosity, and commitment (Hardy and Van Vugt 2006; Willer 2009). Existing research in online reviews lends support to the theory of competitive altruism: survey studies consistently show that an important motivation for writing online reviews is the pursuit of attention, status, and superiority (Huang et al. 2016; Pan and Zhang 2011; Wang et al. 2017).

Compared to pure altruism, competitive altruism holds a very different implication for the effect of friend contributions. Research suggests that social contacts are especially helpful for gaining status (Anderson and Kilduff 2009). With a large social group, an individual's altruistic contributions can easily

[5] Although the term "competitive altruism" is relatively new, a few key elements of the theory (e.g., individual's care for status as a driving force for altruistic contribution) have been previously noted in Bernheim's (1994) theory of conformity and Milinski et al.'s (2002) use of reputation to solve the tragedy of the commons. The theory's predictions are also consistent with empirical findings that status competition can provide strong motivations for voluntary giving (Donath 2002; Jones et al. 1997) and contribution in online communities (Levina and Arriaga 2014; Wasko and Faraj 2005).

go unnoticed by random strangers. Online friends, on the other hand, are more likely to pay attention to a user's contribution and provide favorable appraisals because of their shared interests and personal connection with the focal user. Therefore, online friends would be more helpful for a user's pursuit of status. In addition, friend contributions can serve as a "beacon" for altruistic contributions: Existing friend contributions suggest that contributing a review of this restaurant is socially desirable and would enhance the user's commitment to her social group. In contrast, existing stranger contributions do not offer such added benefits. Therefore, competitive altruism predicts a positive effect of friend contributions: A user is more likely to offer her review after observing a friend review, compared to a stranger review.

Despite the different predictions of pure and competitive altruism, they may not be mutually exclusive. A user motivated mainly by competitive altruism may still have concerns with being redundant after a friend's contribution; conversely, a user whose main goal is to help others may still value the status-building benefits of contributing after a friend. In our research context, though, we expect the effect of competitive altruism to dominate because of a strong user community and status system on Yelp. First, the platform and its users have invested strongly in community building. Second, as described earlier, Yelp has an elaborate community-driven status system. Each year, the community selects new elite users based on community votes and peer nominations. Lastly, Yelp and the user community provide enhanced status benefits. Elite users not only enjoy prestige within the community, but also perks offered by store owners and/or the platform. Even earning a local status can have benefits. Even non-elite users can benefit from enhanced status: e.g., they would have a higher chance of being invited to official events for all Yelp users and private gatherings. Therefore, we expect the prediction of competitive altruism will prevail, leading to a positive effect of friends' reviews.

H1: *Holding the total number of recent reviews constant, a user's likelihood to review a restaurant increases with the number of recent reviews posted by her friends on that restaurant.*

In addition, we explored two variables that might moderate our main hypothesis: store popularity (as measured by the number of existing reviews) and the user's reviewing experience. We argue that pure and competitive altruism can hold different implications for such moderating effects. Due to the exploratory nature of our arguments, however, we do not offer formal hypotheses.

From the perspective of pure altruism, when a restaurant has more existing reviews, each additional review adds less value. Though a friend review is a stronger substitute for the focal user's review than a stranger review, both have a diminishing effect as the restaurant has more existing reviews. Therefore, the additional (negative) substitution effect of a friend review also diminishes with more existing reviews, implying the effect of friend reviews to increase with the number of existing reviews. If the focal user has more experience in writing reviews, her contribution would be higher, and the substitution effect of a friend review would be weakened, suggesting an increase in the effect of friend reviews.

From the perspective of competitive altruism, when a restaurant has more reviews, contributing an additional review after a friend is less helpful for status building. This is because such a contribution is less distinctive and less helpful for the social group to distinguish itself (Levina and Arriaga 2014). Therefore, the positive effect of contributing after a friend contribution is reduced. A more experienced user, because of her higher status, is less eager to impress her friends. Therefore, we expect the positive effect of friend contributions to be weaker for more experienced users.

In sum, pure and competitive altruism lead to different predictions on moderating effects. Again, noting the strength of community and status system in our setting, we expect the predictions of competitive altruism to prevail, though acknowledging that the forces of pure and competitive altruism may coexist.

3.2. Effect of Friend Contributions on Review Quality

Pure altruism theory suggests that, after a friend's contribution, the marginal value of another contribution decreases. This leads to a lower effort by the focal user, which could result in a lower quality review. On the other hand, competitive altruism suggests that individuals contribute reviews as a way of gaining status, and they will do so in ways that suggest a high level of competence and generosity (Anderson and Kilduff 2009). When a user offers a review after a friend, she knows her friends will pay close attention, so she will put in more effort to produce a high-quality review to impress her friends. In this way, friends can bring out the best in the user. Similar to Hypothesis 1, we expect that the prediction of competitive altruism will prevail in our context, leading to a positive effect of a friend contribution on subsequent contribution's quality, and such an effect would increase with the number of friend contributions.

H2: *Holding the total number of recent reviews constant, the quality of a user's review of a restaurant increases with the number of recent reviews posted by her friends on that restaurant.*

4. Research Context and Data

We collected our data from Yelp, one of the largest and most successful online review platforms in the world. Yelp operates as a platform for user-generated reviews for local businesses such as restaurants and schools. Only registered users can write reviews. Each registered user has a public profile that includes information such as the user's name, location, reviews written, friends, bookmarks, and compliments received (See the Online Appendix for details). Yelp has extensive support for social networking. Users can also vote on existing reviews (no login required) written by others on three dimensions: useful, funny, and cool (Figure 1). Users can also follow other users and send compliments to them. A user can request to become friends with other users.[6] Once the friend request is confirmed, users can receive updates on the friend's activities, such as the friend's reviews and photos, via the "friends" section of their private homepage (Figure 1a). Friend reviews will also appear on top of the review list on a business page (Figure 1b). Yelp does not send notifications of friend reviews to users.

To encourage contributions and community building, Yelp Elite Council selects elite reviewers each year who are deemed stellar community members and role models. The selection is based on peer nominations and take into account the quantity and quality (votes) of one's contributions.[7] Elite users are honored with a badge on their profile. Yelp elites enjoy many tangible benefits including invitations (with guest passes) to free Yelp Elite events and tasting events organized by businesses.

[6] Such "online friends" are typically formed based on shared personal interests, and use electronic connection and communication as a primary form of interaction with each other (Dennis et al. 1998; Hiltz and Wellman 1997; Ridings and Gefen 2006).
[7] According to a Yelp blog article (https://www.yelpblog.com/2012/01/what-makes-a-yelper-elite), Yelp does not have a published checklist for its Elite criteria. Unofficial sources suggest that elite users are selected based on their last year's review contributions (both quantity and quality), and their engagement with the community, as reflected by their activities such as sending compliments, casting votes, and answering questions. The Elite status is not permanent. A user must earn the Elite badge each year.

We collected data on restaurant reviews in the state of Washington (WA) between March 2013 and November 2013.[8] To obtain a list of users in the WA area who write restaurant reviews, we started with all 551 elite users located in Seattle, WA, then obtained their friend lists, which resulted in 33,815 users. Among the 33,815 elite users' friends, we selected our study sample as those who were (1) located in WA (11,637), and (2) active (i.e., wrote at least one review on WA restaurants) during our study period (3,630).[9] The resulting set of 2,923 users accounts for 78% of all users who meet the two criteria,[10] suggesting that we have a fairly comprehensive list of users.

For each user in our study sample, we revisited the user's profile and list of friends every month between March 2013 and April 2014. We also collected all their reviews, bookmarks, and compliments received since March 2012. To ensure that we had complete data on reviews, we separately collected a total of 109,402 reviews on all 8,289 WA restaurants generated during our study period.

5. Analysis on Review Quantity

5.1. Dataset, Model, and Variables

To test the effect of friend reviews on review quantity, we constructed a user × restaurant × period (week) panel in the following way. First, we intersected the 8,289 WA restaurants with 2,923 users to obtain 24,228,747 user-restaurant pairs. Among all user-restaurant pairs, 18,387 user-restaurant pairs were *events* (i.e., the user wrote a review for the restaurant during our study period). Because events were rare in our data, we sampled all available events and a tiny fraction of nonevents, and used weighting to correct the estimated coefficients (King and Zeng 2001). Specifically, we kept all events and randomly sampled five times the number of events, without replacement, from available nonevents (we also tested sampling three and seven times the number of events and obtained similar results). We then intersected the resulting 110,322 user-restaurant pairs with 36 periods to obtain 3,971,592 user-restaurant-period triples. Finally, we

[8] We picked the WA area because the number of restaurants and the number of reviews per month in this area are close to the average among 21 metropolitan areas featured on the front page of Yelp (Wang 2010).
[9] A robustness test including inactive users yields consistent results (see the Online Appendix). It is worth noting that, even in the current sample, there are cases where the focal user had not written any review before period t.
[10] Over time, we collected all users who wrote a review on any of the 8,289 WA restaurants in our dataset, or who are either friends, or friends of friends of the 551 elite users. Among the resulting 1,197,043 users at the end of our data collection, a total of 3,748 users were located in WA and had written at least one review on a WA restaurant during our study period.

dropped cases where users had already written a review for the given restaurant, and obtained 3,663,479 cases for our analysis.

Our dependent variable, $Review_{ijt}$, is a binary indicator of whether user *i* wrote a review on restaurant *j* in period *t* (i.e., whether user *i* survives in period *t*). Because a user can submit at most one review per restaurant,[11] and the panel consisted of discrete periods, we adopted a discrete-time survival model for our data, where an event is a review. The discrete-time survival model is equivalent to the logit model; the discrete-time hazard is the odds of dying (i.e., writing a review) conditional on survival up to that point.

Logit models are known to sharply underestimate event probabilities in samples with less than 200 events (King and Zeng 2001). To avoid such a bias, we adopted Rare Event logit (ReLogit) (King and Zeng, 2001, 2002) and used logit as a backup.

A potential confound of friend-contribution effects is homophily: A pair of friends independently chose to review the same restaurant because of their similar preferences. To control for homophily, we follow Wang et al. (2018) to include the number of reviews written by future friends as a control. Future friends share similar preferences with the focal user, but future-friend reviews would not have influenced the focal user. Any effect of a future-friend review is a result of homophily only. If the effect of a current-friend review exceeds that of a future-friend review, we can infer the influence of friend contribution beyond homophily.

Formally, we assume the utility for user *i* to write a review on restaurant *j* in period *t*, U_{ijt}, is a function of the numbers of reviews written by current friends ($CurFrndReviews_{i,j,t-1}$), future friends ($FutFrndReviews_{i,j,t-1}$), and anyone ($NewReviews_{j,t-1}$) on restaurant *j* in period *t-1*, additional control variables, and an i.i.d. random component ε_{ijt} with a type-I extreme value distribution.

$$U_{ijt} = \beta_1 CurFrndReviews_{i,j,t-1} + \beta_2 FutFrndReviews_{i,j,t-1} + \beta_3 NewReviews_{j,t-1} + \gamma Controls_{i,j,t-1} + \varepsilon_{ijt} \qquad (1)$$

[11] Yelp allows users to update their reviews at a later time, but such update incidents are rare. We focus on initial reviews because we are interested in whether users decide to offer a review.

Control variables. We included an extensive list of control variables (see Table 1 for a description). We first controlled for several user characteristics. Following Wang (2010), we controlled for the number of compliments sent and received *(#Compliments*), and the number of friends (*Log#Friends*). We used the number of reviews by the user in the last period *(#SelfReviews*) and the number of cumulative reviews by the user up to the last period (*Log#CumSelfReview*) to control for a user's tendency to write reviews. To control for the life cycle of users on the platform, we included tenure on the platform (*LogTenure*). We also controlled for a number of other user characteristics including elite status (*Elite*), gender (*Female*), and estimated income *(CityIncome).*[12] The estimated income was approximated by the median household income of the city where the user lives. We used the distance between users and restaurants to capture geographical proximity (*Dist*).

We controlled for a number of restaurant characteristics that may affect a user's review decision, including the restaurant's average rating (*AvgRatingRestaurant*), variance of existing ratings (*AvgVariRestaurant*), and cumulative reviews (*Log#CumReviews*) because prior research suggested that these affect the quantity of new reviews (Moe and Schweidel 2012). We also included price range (*Price*) coded from levels 1 through 4 based on Yelp reported price ranges ($ to $$$$), whether the restaurant page has been claimed by its owner (a claimed store more likely listens to online reviews, which may encourage users to submit reviews) (*Claimed*), restaurant categories (*16 latent category dummies*), and whether the restaurant was promoted by Yelp (*Promoted*). The variable *Promoted* indicates whether the restaurant was featured in the Yelp weekly email to users in period *t-1*. This variable allows us to control for marketing campaign effects. We coded restaurant categories by feeding documents of raw restaurant categories, one per restaurant, into a Latent Dirichlet Allocation (LDA) algorithm to recover the underlying latent categories (16 of them) and the mapping of restaurants into latent categories (See the Online Appendix for

[12] We inferred gender from the users' reported first names using Behind the Name's database (https://www.behindthename.com) that lists 21,100+ names and their genders. There are 134 cases where the first names were not in the database or gender ambiguous. We asked two research assistants to independently code the 134 cases based on users' profile photos. Among these, there were eight cases where profile photos did not provide any gender information (e.g., foods, pets). The intercoder reliability was 0.95. We also validated our automatically coded gender by randomly sampling 100 users and comparing them with manual coding based on profile photos. The accuracy of automatic coding was 98%, which we deemed as adequate.

details). Finally, to control for temporal shocks to review quantity, we included month dummies. Table 1 provides summary statistics of the dataset.

5.2. Main Results on Review Quantity

Prior to estimating the models, we conducted collinearity tests and found no signs of collinearity (VIF < 3). We estimated three models, starting with only control variables, then adding current friends' reviews and new reviews in the last period, and finally adding future-friends' reviews. We ran both ReLogit and logit models with weighting adjustments. The results are shown in Table 2. Because the results are consistent across models, we omit Logit-1 and Logit-2 for brevity and report the results of ReLogit-3.

CurFrndReviews has a positive effect (*OR* = 2.95, $p < 0.001$, OR for odds ratio). *FutFrndReviews* also has a positive effect (*OR* = 1.87, $p < 0.001$), but smaller than that of *CurFrndReviews*. An F-test comparing the odds ratios for *CurFrndReviews* and *FutFrndReviews* is significant ($F = 7.81$, $p = 0.005$), indicating the existence of friend effects beyond homophily. Thus ***Hypothesis 1*** is supported.

Compared with current friend's reviews, *NewReviews*, which captures the effect of stranger reviews, has a much smaller effect (*OR* = 1.10, $p < 0.001$). The effect of *CurFrndReviews* (*OR* = 2.95) is comparable to that of reviews promoted in Yelp's weekly newsletters (*OR* = 2.73), suggesting a strong effect of friend reviews. We further computed the predicted probabilities of focal users writing a review when *CurFrndReviews* equals 0 (i.e., no friend review) and 1 (i.e., one friend review), holding all other predictors at their means. We find that the probability of writing a review is ***three times higher*** when there is a friend review, compared with no friend review (0.0000225/0.00000765).

The effects of most control variables are in the expected directions. *Log#Compliments* has a positive effect, suggesting that socially active users are more likely to provide reviews. Both *#SelfReviews* and *Log#CumSelfReview* have a positive impact, demonstrating that productive users tend to write more reviews. As expected, *Elite* and *CityIncome* have a positive effect, whereas *LogTenure* and *Dist* have a negative effect. *Log#Friends* has a negative impact, suggesting that having more friends, while fixing the number of friend reviews on the restaurant, is negatively associated with the user's probability of reviewing the restaurant. This finding is consistent with conformity: When a user observes that a larger proportion of friends do not contribute, she is more likely to conform to the norm of not contributing (Carpenter 2004). Consistent with Moe and Schweidel (2012), *AvgRatingRestaurant* and *Log#CumReviews* both have a positive impact, demonstrating that users tend to review highly-rated and often-reviewed restaurants. *AvgVariRestaurant* has a negative effect, suggesting that users are less likely to review the restaurants if prior users have very different opinions. This is consistent with prior findings that consumers avoid visiting restaurants with high uncertainty in quality (Wu et al. 2015). *Promoted*, *Claimed*, and *Price* all have a positive impact.

In the last two columns of Table 2, we further show that the effect of friend reviews decreases with store popularity (measured by log number of existing reviews, *Log#CumReview*) (a plot of this effect is available in the Online Appendix) and the focal user's reviewing experience (measured by log number of past reviews, *Log#CumSelfReview*), suggesting the friend-contribution-cue approach has a strong effect for "long-tail" restaurants and less-experienced users. We report several robustness tests in the Online Appendix, including (a) three ways of validating that future-friends' reviews are a good proxy for homophily, (b) evidence that observed effects cannot be explained by awareness effects alone or by friends going to restaurants together, (c) consistent results when including older friend reviews and inactive users.

6. Analysis on Review Quality

6.1. Effect of Friend Contributions on Votes

Review quality reflects a consumer's evaluation of how useful a particular review is in assisting a purchase decision. We used several different measures of review quality. The literature on review quality has predominantly used helpfulness votes received by a review as a proxy for review quality (e.g., Burtch et al. 2018; Otterbacher 2009; Wang et al. 2017). Following the literature, we first used votes to measure review quality. Yelp has three kinds of votes: *useful*, *funny*, and *cool*. We constructed two vote-based measures of the review quality: combined votes (*LogCombinedVotes*) and useful votes only (*LogUsefulVotes*).

We constructed a user-restaurant panel consisting of users who have offered a review for the restaurants. We used *CurFrndReviews* and *NewReviews* as independent variables and added *ReviewAge* to control for the effect that older reviews have more time to get votes.[13] We also included many restaurant attributes and dynamic user attributes as controls. We estimated a panel-OLS model with user fixed effects.

We first estimated a model with only control variables, then added *CurFrndReviews* and *NewReviews*. Our fixed-effect panel-OLS results are reported in Table 3 (M1-M4). As shown in M2 and M4, the coefficients for *CurFrndReviews* are positive and significant, suggesting that friend reviews have a positive effect on the quality of review contributed by the focal user, supporting ***Hypothesis 2***.

6.2. Effect of Friend Contributions on Turker Ratings of Review Quality

Because votes can be biased by extraneous factors unrelated to review quality, such as the order in which reviews are displayed or the social relations between voters and the reviewer, we implemented an alternative measure of review quality by asking Amazon Mechanical Turk workers, or "Turkers," to rate the quality of reviews on a 5-point scale (1 = low quality, 5 = high quality). Instead of rating all reviews, which is costly, we selected carefully matched pairs of reviews. Specifically, we identified all users who have written two reviews: one preceded by exactly one friend review in period *t-1*, no stranger review in period *t*-1 and no friend review in prior periods (*AfterFrndReview*=1); one preceded by exactly one stranger review in period *t-1*, no friend review in period *t-1* and no friend review in prior periods (*AfterFrndReview*=0). This design resulted in 52 users and 104 reviews. We obtained four Turker ratings per review (see the Online Appendix for details). We ran an OLS model with user fixed-effects to control for user-specific effects on review quality. Our results, reported in Table 4, show that the coefficient of *AfterFrndReview* is positive and significant, suggesting that exposure to a friend review resulted in a higher-quality review than exposure to a stranger review. This lends further support for ***Hypothesis 2***.

[13] Additionally, to ensure all reviews had enough time to gather votes, we collected the votes of all reviews 2 years after the most recent reviews in our dataset were written.

6.3. Effect of Friend Contributions on Review Novelty

If a review's content overlaps significantly with existing reviews, the review does not provide additional information for consumers, and is judged to be of lower quality. To capture this dimension of review quality, we calculated a *novelty score*, based on the cosine distance between the Latent-Semantic-Analysis-based representations of the focal and prior reviews of the same restaurant (see the Online Appendix for details). We replicated our analysis on votes with novelty score as the dependent variable. Our results (Table 3, M5 and M6) show that *CurFrndReviews* has a positive effect on review novelty, lending further support to ***Hypothesis 2***. In the Online Appendix, we further show that our results hold if we use review length as the dependent variable or include older friend reviews.

7. Discussion and Implications

Motivated by under-provision, quality degradation, and imbalances of online reviews, we investigate whether an online review platform can use friend-contribution cues to motivate users to write more and higher-quality reviews. We find friend contributions to have a positive effect on users' tendency to contribute and the quality of the resulting reviews. Users are three times more likely to provide a review after a friend has written one on the same restaurant, and this effect cannot be solely explained by homophily or awareness. Interestingly, friend reviews have a stronger effect on less-reviewed stores and less-experienced users. Reviews written after a friend's review are of higher quality, longer, and more novel.

7.1. Contributions to the Literature

This research makes two main contributions. First, building on theories of public goods, we developed a novel theoretical understanding of users' contribution behaviors under friend influence on online user communities as Yelp. Pure altruism holds that contributions are motivated by concerns of others' welfare whereas competitive altruism holds that the pursuit of status can motivate altruistic contributions. We extended these theoretical perspectives to study the effect of friend-contribution cues and obtained a few distinct predictions that were supported by our empirical findings. These include: (1) users respond to friend-contribution cues by increasing their own contributions, despite the incentive to free-ride; (2) the effect of friend-contribution cues is stronger for less-reviewed restaurants and less-experienced users; (3) friend-contribution cues lead to higher quality reviews. Overall, we found competitive altruism to be a useful theoretical lens for understanding the private provision of public goods in an online community such as Yelp. We believe such a theoretical perspective can offer new insights for other communities of user-generated content.

Second, we contribute to the literature of online reviews by identifying a "friend-contribution-cue" approach to promoting more and higher-quality reviews. Our approach complements the existing approaches (Burtch et al. 2018; Chen et al. 2010) by allowing ORPs to leverage social relations among users. Users who are exposed to reviews written by their online friends are three times more likely to offer a review, and such a review tends to be longer, more novel, and generates more votes. Importantly, the friend-contribution-cue approach is more effective for less-reviewed products/services and less-experienced users, suggesting its potential for mitigating imbalances in online reviews and motivating occasional contributors. These combined benefits address important gaps in existing approaches for motivating reviewer contributions.

7.2. Managerial Implications

Our findings suggest that, to increase quantity and quality of review production, vendors and platforms should leverage social networks among users by highlighting recent reviews contributed by their friends. Our analysis suggests that the effect of friend contributions is comparable to the promoted reviews in Yelp's weekly newsletters (Table 2). For the most effective results, vendors and platforms should target products/services that have few reviews and less-experienced users. Our results also suggest the value of promoting/facilitating competitive altruism in the volunteer reviewer community. This might include: (1) instituting a community-driven process for selecting outstanding contributors; (2) selecting the outstanding contributors based on altruistic contributions and commitment; and, (3) offering complimentary community-based rewards for outstanding contributors (e.g., dinner parties, tasting events, and privilege within the community). One caveat when using friend reviews is Wang et al. (2018)'s finding that friend influence may increase biases in review ratings. Platforms should be aware of such a potential downside and take steps to mitigate it, such as by favoring independent reviews when aggregating ratings.

7.3. Limitations and Future Research

This study has several limitations. Although we have controlled for homophily and many other factors, we cannot completely rule out the possibility of unobserved events driving both friend contributions and focal users' contributions. Randomized field experiments can help alleviate such concerns. Second, we do not have data to further delineate the effects of friend contributions by stages of a user's journey. We present evidence that the observed effect cannot be explained by increased awareness alone, but further research is needed. Third, our reliance on a popular snowballing-sampling approach may introduce biases, despite the fact that our sample covers nearly 80% of target users. Fourth, we do not have data to measure whether the users actually read the friend reviews. We present evidence that users only act on the friend review written in the last period, not before. However, we do not know if this non-effect of the friend reviews prior to the last period is because users read them but not are influenced by them, or if they do not read them. Further research on this is needed. Fifth, though we believe competitive altruism provides the best holistic framework for explaining our findings, there could be alternative theoretical explanations. As we earlier noted (in footnotes 4 and 5), competitive altruism intersects with other theoretical traditions that can be further differentiated in future research. Finally, with appropriate data, future research can extend this study by examining how friend-contribution cues affect contribution to other restaurants.

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Table 1: Descriptive Statistics of Variables (N = 3,663,479)

Variables	Definition	Mean	Std. Dev	Min	Max
$Review_{ijt}$	Whether user *i* writes a review on restaurant *j* in period *t*: yes 1; otherwise 0	0.01	0.07	0.00	1.00
$CurFrndReviews_{i,j,t-1}$	# current-friend reviews of user *i* on restaurant *j* in period *t-1*	0.00	0.03	0.00	5.00
$FutFrndReviews_{i,j,t-1}$	# future-friend reviews of user *i* on restaurant *j* in period *t-1*	0.00	0.02	0.00	5.00
$NewReviews_{j,t-1}$	# new reviews on restaurant *j* in period *t-1*	0.42	1.06	0.00	38.00
$Log\#Compliments_{i,t-1}$	Log # of compliments sent and received by user *i* in period *t-1*	0.11	0.43	0.00	5.38
$\#SelfReviews_{i,t-1}$	# of reviews written by user *i* in period *t-1*	0.21	0.90	0.00	42.00
$Log\#CumSelfReview_{i,t-1}$	Log # cumulative reviews by user *i* up to period *t-1*	3.99	1.35	0.00	7.37
$LogTenure_{i,t-1}$	Log days elapsed since user *i* registered on Yelp up to period *t-1*	7.09	0.52	3.85	8.03
$Log\#Friends_{i,t-1}$	Log (1+ # friends of user *i* in period *t-1*)	3.52	1.08	1.10	7.00
$Elite_{i}$	Whether user *i* is an elite user	0.36	0.48	0.00	1.00
$Female_{i}$	Whether user *i* is female	0.45	0.50	0.00	1.00
$CityIncome_{i}$	Median household income (thousands of dollars) of the city user *i* lives	69.37	13.72	24.49	192.25
$Dist_{i,j}$	Miles between restaurant *j* and the city where user *i* lives	50.35	66.57	0.00	439.94
$AvgRatingRestaurant_{j,t-1}$	Cumulative average rating of restaurant *j* up to period *t-1*	3.59	0.69	0.50	5.00

AvgVariRestaurant $_{j,t-1}$	Variance of cumulative ratings of restaurant *j* up to period *t-1*	1.07	0.30	0.00	2.00
Log#CumReviews $_{j,t-1}$	Log # cumulative reviews of restaurant *j* up to period *t-1*	3.42	1.24	0.00	7.85
Promoted $_{j,t-1}$	Whether restaurant *j* is promoted in period *t-1*	0.00	0.02	0.00	1.00
Claimed $_{j,t-1}$	Whether restaurant *j*'s business page on Yelp is claimed in period *t-1*	0.66	0.47	0.00	1.00
Price $_{j}$	Price range of restaurant *j*: 1 - least expensive; 4 - most expensive	1.62	0.56	1.00	4.00

We omit the summary statistics of 8-month dummies and 16 restaurant-category dummies for brevity.

Table 2. Effect of Friend Contributions on Review Quantity – Discrete-time Hazard Models

Independent Variables	ReLogit-1	ReLogit-2	ReLogit-3	Logit-3	Restaurant Popularity	User Experience
	OR (SE)					
CurFrndReviews $_{i,j,t-1}$		2.949***	2.950***	2.943***	20.338***	9.122***
		(0.240)	(0.238)	(0.238)	(8.283)	(3.790)
NewReviews $_{j,t-1}$		1.095***	1.095***	1.095***	1.094***	1.095***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
CurFrndReviews $_{i,j,t-1}$ *Log#CumReviews $_{j,t-1}$					0.667***	
					(0.053)	
CurFrndReviews $_{i,j,t-1}$ *Log#CumSelfReview $_{j,t-1}$						0.814**
						-0.063
FutFrndReviews $_{i,j,t-1}$			1.870***	1.843***	1.861***	1.831***
			(0.267)	(0.263)	(0.265)	(0.262)
Log#Compliments $_{i,t-1}$	1.355***	1.344***	1.341***	1.341***	1.338***	1.342***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
#SelfReviews $_{i,t-1}$	1.120***	1.121***	1.120***	1.120***	1.120***	1.120***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log#CumSelfReview $_{i,t-1}$	1.456***	1.451***	1.451***	1.451***	1.451***	1.454***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
LogTenure $_{i,t-1}$	0.722***	0.718***	0.718***	0.718***	0.718***	0.718***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Log#Friends $_{i,t-1}$	0.912***	0.913***	0.913***	0.913***	0.914***	0.912***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Elite $_{i}$	2.001***	1.989***	1.989***	1.989***	1.990***	1.986***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Female $_{i}$	0.980	0.972+	0.972+	0.972+	0.973+	0.972+
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
CityIncome $_{i}$	1.001+	1.001*	1.001*	1.001*	1.001*	1.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dist $_{i,j}$	0.983***	0.982***	0.982***	0.982***	0.982***	0.982***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
AvgRatingRestaurant $_{j,t-1}$	1.216***	1.197***	1.197***	1.197***	1.196***	1.196***
	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
AvgVariRestaurant $_{j,t-1}$	0.631***	0.702***	0.703***	0.703***	0.698***	0.704***
	(0.025)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Log#CumReviews $_{j,t-1}$	1.731***	1.584***	1.583***	1.583***	1.594***	1.582***

	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Promoted $_{j,t-1}$	2.913***	2.725***	2.727***	2.700***	2.693***	2.699***
	(0.434)	(0.407)	(0.407)	(0.403)	(0.402)	(0.403)
Claimed $_{j,t-1}$	1.110***	1.119***	1.120***	1.120***	1.119***	1.120***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Price $_{j}$	1.251***	1.266***	1.266***	1.266***	1.263***	1.266***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Month & Restaurant category dummies	included	included	included	included	included	included
Log-Likelihood	-200,055	-199,524	-199,514	-199,514	-199,476	-199,509
Pseudo R-squared	0.075	0.077	0.077	0.077	0.077	0.077
N	3,663,479	3,663,479	3,663,479	3,663,479	3,663,479	3,663,479

DV = whether user *i* reviews restaurant *j* in period *t* ($Review_{ijt}$). The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001.

Table 3. Effect of Friend Contributions on Review Quality – Fixed-Effect OLS

	DV = Log Combined Votes Received *(LogCombinedVotes)*		**DV = Log Useful Votes Received *(LogUsefulVotes)***		**DV = Novelty *(Novelty)***	
Independent Variables	**M1**	**M2**	**M3**	**M 4**	**M5**	**M6**
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
CurFrndReviews $_{i,j,t-1}$	-	0.1084*	-	0.0928*	-	0.000795**
	-	(0.0484)	-	(0.0388)	-	(0.000293)
NewReviews $_{j,t-1}$	-	0.0080*	-	0.0063*	-	-0.000137***
	-	(0.0034)	-	(0.0027)	-	(0.000036)
ReviewAge $_{i,j,t}$	-0.0005	-0.0006	-0.0004	-0.0004	-	-
	(0.0008)	(0.0008)	(0.0007)	(0.0007)	-	-
Log#Compliments $_{i,t-1}$	0.0432**	0.0428**	0.0334**	0.0331**	0.000005	0.000001
	(0.0159)	(0.0159)	(0.0128)	(0.0128)	(0.000119)	(0.000120)
#SelfReviews $_{i,t-1}$	0.0063+	0.0062+	0.0030	0.0029	0.000048**	0.000048**
	(0.0033)	(0.0033)	(0.0023)	(0.0023)	(0.000018)	(0.000018)
Log#CumSelfReview $_{i,t-1}$	0.0641	0.0627	0.0379	0.0367	0.000459	0.000445
	(0.0579)	(0.0577)	(0.0490)	(0.0489)	(0.000499)	(0.000502)
LogTenure $_{i,t-1}$	-0.2188	-0.2206	-0.1034	-0.1049	-0.002102*	-0.002094*
	(0.1910)	(0.1919)	(0.1545)	(0.1552)	(0.000963)	(0.000961)
Log#Friends $_{i,t-1}$	0.1648*	0.1682**	0.1149*	0.1177*	-0.000246	-0.000262
	(0.0649)	(0.0652)	(0.0559)	(0.0561)	(0.000407)	(0.000413)
AvgRatingRestaurant $_{j,t-1}$	0.0411**	0.0413**	0.0186+	0.0187+	0.000144	0.000150
	(0.0130)	(0.0130)	(0.0107)	(0.0107)	(0.000102)	(0.000102)
AvgVariRestaurant $_{j,t-1}$	-0.0269	-0.0186	-0.0063	0.0004	0.000849***	0.000738***
	(0.0342)	(0.0342)	(0.0279)	(0.0280)	(0.000199)	(0.000198)
Log#CumReviews $_{j,t-1}$	-0.0384***	-0.0440***	-0.0404***	-0.0448***	-0.001287***	-0.001192***
	(0.0059)	(0.0063)	(0.0046)	(0.0050)	(0.000058)	(0.000060)
Promoted $_{j,t-1}$	0.1912+	0.1767+	0.1293	0.1177	-0.002082	-0.001887
	(0.1065)	(0.1048)	(0.0827)	(0.0817)	(0.002265)	(0.002270)

Claimed $_{j,t-1}$	0.0159	0.0165	0.0212+	0.0216+	0.000021	0.000014
	(0.0150)	(0.0150)	(0.0123)	(0.0123)	(0.000148)	(0.000148)
Price $_{j}$	0.0929***	0.0926***	0.0856***	0.0854***	0.001473***	0.001475***
	(0.0136)	(0.0136)	(0.0111)	(0.0111)	(0.000132)	(0.000132)
Constant	1.4481	1.4597	0.7563	0.7660	1.009533***	1.009450***
	(1.2647)	(1.2691)	(1.0176)	(1.0218)	(0.006392)	(0.006369)
Month & restaurant-category dummies	included	included	included	included	included	included
Log-Likelihood	-17884.75	-17874.85	-13925.06	-13914.88	67347.28	67363.72
Adjusted R-squared	0.459	0.460	0.396	0.397	0.126	0.128
N	18,387	18,387	18,387	18,387	18,340	18,340

The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001. The sample size for the last two columns was smaller because we cannot compute novelty scores for the first review.

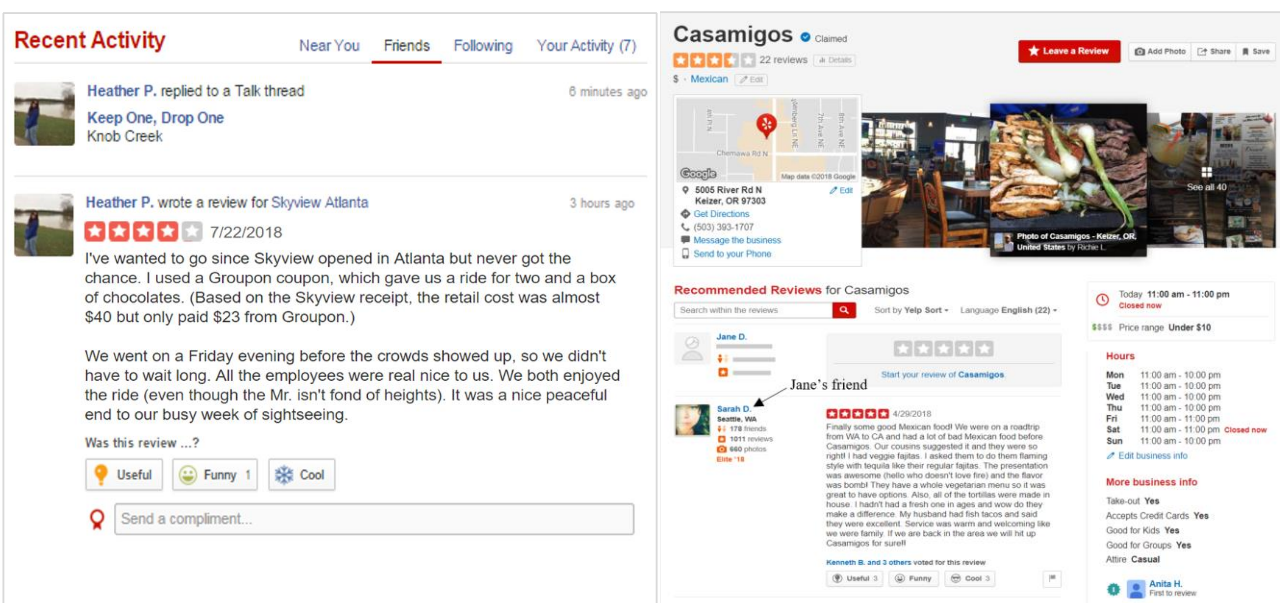
Table 4. Effect of Friend Contributions on Turker-Rated Review Quality– Fixed-Effect OLS

Independent Variables	Coefficient (SE)
AfterFrndReview	0.346*
	(0.112)
Constant	3.240***
	(0.079)
Log-Likelihood	-617.33
Adjusted R-squared	0.165
N	416

DV= user *i*' review quality on restaurant *j* (*Quality*). The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001.

Figure 1. Examples of Friend Reviews on Yelp

(a) Friend Review Feeds on a Private Homepage (b). A Friend Review Featured on a Business Page



Do Friends Bring Out the Best in Us?

The Effect of Friend Contributions on Online Review Provision

Online Appendix

Figure A1. An Example of a Yelp User's Public Profile Page

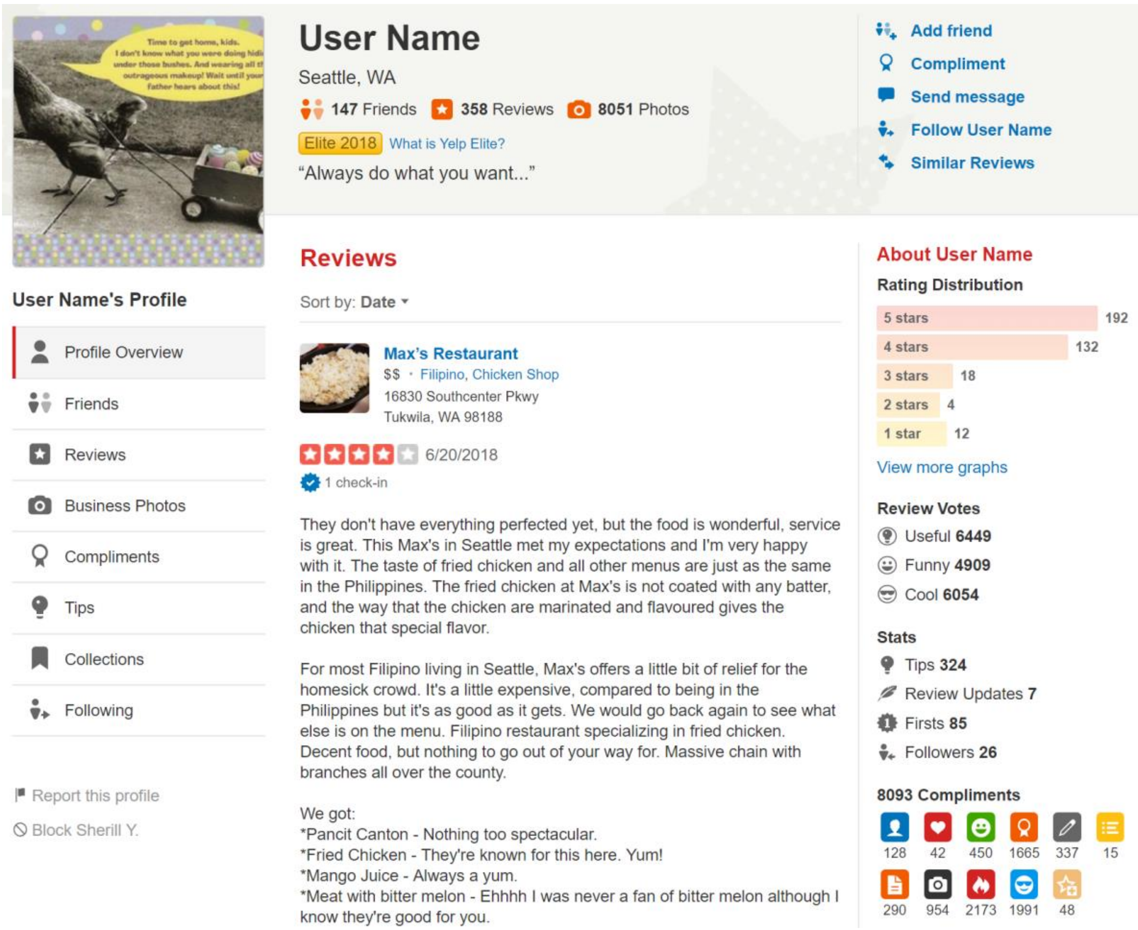
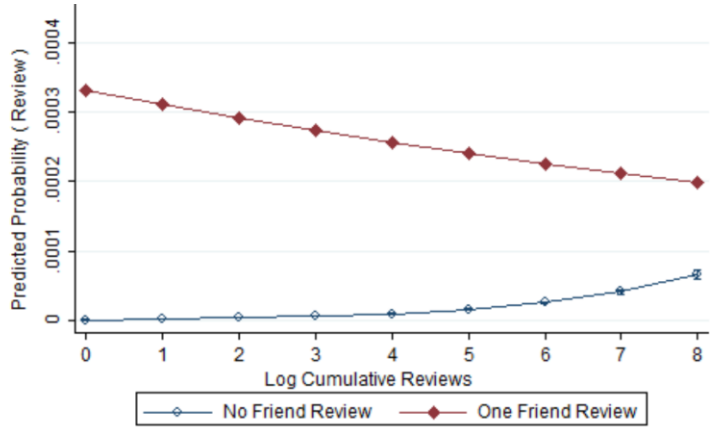


Figure A2. Marginal Effect of Current-Friend Reviews as a Function of Cumulative Reviews



1. Turker Ratings of Review Quality

To ensure the reliability of Turker ratings, we selected U.S. Turkers with over 95% task acceptance rates and at least 50 completed assignments. We paid them $3 for rating approximately 12 reviews. For each review, we randomly assigned four different Turkers without informing them of the review group. To ensure that Turkers pay attention to the rating task, we asked them to justify the rating they gave. Seven Turkers who failed to justify their answers were removed. The average Intraclass Correlation Coefficient was 0.9904. Therefore, we find an excellent degree of inter-rater reliability, suggesting that Turkers are highly consistent in their evaluation of review quality.

2. Novelty Score Calculation

To calculate the review novelty, we applied a standard cosine distance to document embeddings in the semantic space. We built the semantic space using the classical LSA approach, which is a count-based method that applies SVD to the TFIDF-weighted term-document matrix. We first built the term-document matrix using the whole corpus of documents (reviews), after some preprocessing, including the removal of punctuations, stop words, non-word characters, and stemming. We applied a TFIDF weighting scheme to the term-document matrix to penalize uninformative words. We then utilized SVD to build the embedding space with reduced dimensions, which produced vector embeddings for both words and documents. Finally, we measured the novelty of a review by calculating the smallest cosine distance between the vector embedding for the review and that of any proceeding review of the same store.

3. Restaurant Category Calculation

Each restaurant may be listed under several categories, e.g., "Bakeries / Cupcakes / Desserts / Ice Cream & Frozen Yogurt". There are over 1,000 distinct restaurant categories in our raw data, too many to be included in our analysis. We used Latent Dirichlet Allocation (LDA) to reduce the number of restaurant categories because it can leverage the fact that the raw categories belonging to the same restaurant are likely correlated, and based on the co-occurrence of raw categories, LDA can recover (fewer) latent categories. Following Stevens et al. (2012) and Röder et al. (2015), we chose 16 categories based on the peak coherence score (using an alternative cutoff of 12 categories did not alter our results). The top two keywords for the resulting categories include, for example, "pizza, Italian", "American, traditional", "breakfast, brunch", "food, fast", and "delis, barbeque." Based on the mapping from restaurant to latent categories, we obtained 16 category dummies for each restaurant using a threshold of 0.2 (we also tested the thresholds of 0.1 and 0.3 and obtained similar results).

4. Robustness Checks on Review Quantity

4.1. Are Future-Friends' Reviews a Good Proxy for Homophily?

In our main analysis, we used future-friends' reviews as a proxy for homophily, which relied on an assumption that future friends are as similar to the focal user as current friends. In the present section, we validate this assumption in three ways: (1) comparing the focal user's similarities with current and future friends, (2) restricting both current and future friends to be recent friends to minimize shifts in homophily effects caused by the users' evolving preferences, and (3) comparing effects of friend reviews before and after the friendship formation, which largely holds the homophily effect constant.

Comparing Similarity with Current and Future Friends. A direct way of validating our assumption is to compare the similarity of future friends with that of current friends. We used categories of restaurants in a user's last five reviews to capture the user's preferences (we also used the last three and seven reviews and obtained the same results). For each focal user, we computed, in each period, the similarity between her and 1 randomly selected current friend, and between her and 1 randomly selected future friend based on the categories of the restaurants they reviewed. We used two common similarity measures, Jaccard and Cosine similarity.

Table A1. Similarities with Current and Future Friends

Variables	Jaccard Similarity				Cosine Similarity			
	Mean	**Std Err**	**t**	**p**	**Mean**	**Std Err**	**t**	**p**
Similarity between focal users and **current friends**	0.793	0.0045	0.770	0.441	0.380	0.0043	-4.664	< 0.001
Similarity between focal users and **future friends**	0.789	0.0042			0.407	0.0042		

We conducted paired t-tests to compare similarities between future friends and current friends. The results of t-tests are reported in Table A1. The Jaccard similarity between focal users and their current friends is not significantly different from that between focal users and their future friends. However, future friends are more similar to focal users than current friends by the Cosine measure. This difference is, however, not a cause for concern because if it holds up, we would have overestimated homophily and underestimated the friend effect in our main analysis. Therefore, our main finding is robust to this check.

Restricting to New Friends. One potential reason that future friends may not be as similar to focal users as current friends is that these friendships are formed over time and the user's preference may shift over time. To mitigate this concern, we created a subsample in which there was no more than one current or future friend review, and the current and future friends were formed within 90 days of the beginning of the current period (we also used 60 and 120 days and obtained similar results). This increases the chance that current and future friends are similar, making future friend reviews a better proxy for homophily.

We used the same model as our main analysis, and the results of ReLogit for this subsample are shown in Table A2 (M1). Consistent with the main analysis, *CurFrndReviews* and *FutFrndReviews* both have a positive and significant impact ($p < 0.001$). Similarly, the F-test shows that the odds ratios for *CurFrndReviews* and *FutFrndReviews* are significantly different ($F = 6.91$, $p = 0.009$), suggesting the existence of the friend effect.

Table A2. Two Robustness Checks

Independent Variables	M1: Homophily Check: Restrict to New Friends	M2: Lagged Effect of Friend Reviews
	Odds Ratio	Odds Ratio
	(SE)	(SE)
CurFrndReviews $_{i,j,t-1}$	3.178***	2.465***
	(0.445)	(0.233)
CurFrndReviews $_{i,j,t-2}$	-	2.223***
	-	(0.211)
CurFrndReviews $_{i,j,t-3}$	-	1.943***
	-	(0.207)
NewReviews $_{j,t-1}$	1.097***	1.090***
	(0.004)	(0.005)
FutFrndReviews $_{i,j,t-1}$	1.865***	1.494*
	(0.287)	(0.266)
FutFrndReviews $_{i,j,t-2}$	-	1.978***
	-	(0.307)
FutFrndReviews $_{i,j,t-3}$	-	1.787***
	-	(0.293)
N	3,660,933	3,663,477

We included the same control variables as our main analysis, but omitted them for brevity. Results on control variables are qualitatively the same as our main model. DV = whether user *i* reviews restaurant *j* in period *t* ($Review_{ijt}$). The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Future and Current Friends Being the Same Person. To lend further support to our approach, we also identified user pairs A-B such that B wrote a review on restaurant 1 within 90 days *before* they became friends and a review on restaurant 2 within 90 days *after* they became friends. By contrasting the effects of B's reviews on A before and after they became friends, we held the effect of homophily constant. Because our dataset had a limited number of new friendships, we identified only 84 such pairs of users. As a result, we could only conduct a simpler one-way ANOVA analysis. The ANOVA result shows that the "after" group had a mean number of *Reviews* of 0.29 (SD = 0.46); The "before" group had a mean number of *Reviews* of 0.09 (SD = 0.29). There is a statistically significant difference between the two groups (F (1,82) = 4.97, p = 0.028). This finding lends additional support for our main finding that there is a positive friend effect beyond homophily.

4.2. Effect of Older Friend Reviews

In our main analysis, we only considered the effect of friend reviews in the last period. Friend reviews from previous periods may still have an effect; omitting them may lead to biases. To check the robustness of our results against this possibility, we added friend reviews in periods *t-2* and *t-3* ($CurFrndReviews_{t-2}$, $CurFrndReviews_{t-3}$, $FutFrndReviews_{t-2}$, $FutFrndReviews_{t-3}$) and reran the analyses.

ReLogit results are reported in Table A2 (M2). We find that current- and future-friends' reviews in the last three periods remain significant. The F-tests show that the coefficients for current- and future-friends' reviews in period *t-1* are statistically different (F = 5.99, p = 0.014), but those in periods *t-2* and *t-3* are not (F = 0.42, p = 0.519 and F = 0.19, p = 0.667 respectively). This result suggests that friend reviews in the last period affect a user's tendency to contribute, but not older ones. Thus our main result is robust to this check. Moreover, this finding is consistent with the intuition that recent friend reviews matter more.

4.3. Can Friend Effects Be Explained by Awareness Effects Alone?

One concern in interpreting our findings is that the observed friend effect is because friend reviews were more visible than stranger reviews, leading to an awareness effect, rather than because users respond to friend reviews differently. To rule out this possibility, we leveraged our data on bookmarks. Based on the comments users left when bookmarking, a user bookmarks a restaurant for two main reasons: "to try" and "to review." In both cases, users must have already been aware of the restaurant. If all friend reviews do is only to make users aware of a restaurant, then we would expect friend reviews after bookmarks to have no effect on one's probability of reviewing. To test this idea, we constructed a user × restaurant × period (week) panel with only cases where a user had already bookmarked the restaurant (thus, a friend review, if any, happened after the bookmark). We conducted a similar analysis as our main analysis except that we dropped *FutFrndReviews* because of a lack of variability. Results using this subsample (Table A3) show that the odds ratio for *CurFrndReviews* remained significant and similar to our main finding, indicating that friend reviews have a strong effect beyond generating awareness or intention to review.

Table A3. Effect of Friend Contributions among Bookmarked Restaurants

Independent Variables	Odds Ratio (SE)
$CurFrndReviews_{i,j,t-1}$	2.797***
	(0.755)
$NewReviews_{j,t-1}$	1.045+

	(0.025)
N	372,797

DV = whether user *i* reviews restaurant *j* in period *t* ($Review_{ijt}$).
The values in parentheses are standard errors. Control variables were the same as the main analysis but omitted for brevity. +p<0.10, *p<0.05, **p<0.01, ***p<0.001.

4.4. Can the Observed Effect Be Explained by Friends Going to Restaurants Together?

Another concern is the possibility that friends went to restaurants together, giving the appearance of the friend review causing the focal user's own review. To alleviate this concern, we added a new variable *LocalCurFrndReviews*, defined as the number of reviews written by current friends in period *t-1* who lived in the same city as focal users. If our results were driven by friends going to restaurants together, which is more likely when they are located in the same city, we would expect *LocalCurFrndReviews* to be significant and positive, but not *CurFrndReviews*. ReLogit results (Table A4) show that the odds ratio for *LocalCurFrndReviews* is insignificant, and that for *CurFrndReviews* is significant and similar to our main analysis, indicating that the observed effect is unlikely driven by friends going to restaurants together.

Table A4. Robustness Check – Going to Restaurants Together

Independent Variables	Odds Ratio (SE)
$LocalCurFrndReviews_{i,j,t-1}$	1.069
	(0.181)
$CurFrndReviews_{i,j,t-1}$	2.851***
	(0.313)
$NewReviews_{i,j,t-1}$	1.095***
	(0.004)
$FutFrndReviews_{i,j,t-1}$	1.669*
	(0.335)
N	3,663,479

DV = whether user *i* reviews restaurant *j* in period *t* ($Review_{ijt}$). The values in parentheses are standard errors. Control variables were the same as the main analysis but omitted for brevity. +p<0.10, *p<0.05, **p<0.01, ***p<0.001.

4.5. Inclusion of Inactive Users

Our main analysis of review quantity only included active users (i.e., ones who wrote at least one review during our study period). To further assess the robustness of our results, we matched our sample with an equal number of randomly-sampled inactive user-restaurant pairs, i.e., cases where users never wrote a review during our study period. We intersected these user-restaurant pairs with 36 periods and added the resulting user-restaurant-period triples to our dataset. We re-estimated our main models over this expanded sample. Our results are shown in Table A5, consistent with the results in our main analysis. An F-test comparing the odds ratios for *CurFrndReviews* and *FutFrndReviews* is significant (F = 6.74, p = 0.009), suggesting that our main result on review quantity still holds.

Table A5. Inclusion of Inactive Users

Independent Variables	**ReLogit-1**	**ReLogit-2**	**ReLogit-3**
	OR	OR	OR
	(SE)	(SE)	(SE)
CurFrndReviews $_{i,j,t-1}$		2.918***	2.924***
		(0.246)	(0.245)
NewReviews $_{j,t-1}$		1.097***	1.096***
		(0.004)	(0.004)
FutFrndReviews $_{i,j,t-1}$			1.857***
			(0.287)
Log#Compliments $_{i,t-1}$	1.362***	1.353***	1.349***
	(0.017)	(0.017)	(0.017)
#SelfReviews $_{i,t-1}$	1.126***	1.127***	1.127***
	(0.004)	(0.004)	(0.004)
Log#CumSelfReview $_{i,t-1}$	1.629***	1.625***	1.625***
	(0.014)	(0.014)	(0.014)
LogTenure $_{i,t-1}$	0.702***	0.697***	0.697***
	(0.011)	(0.011)	(0.011)
Log#Friends $_{i,t-1}$	0.899***	0.899***	0.899***
	(0.007)	(0.007)	(0.007)
Elite $_{i}$	3.742***	3.717***	3.717***
	(0.077)	(0.077)	(0.077)
Female $_{i}$	0.988	0.981	0.980
	(0.015)	(0.015)	(0.015)
CityIncome $_{i}$	1.002**	1.002***	1.002***
	(0.001)	(0.001)	(0.001)
Dist $_{i,j}$	0.983***	0.983***	0.983***
	(0.000)	(0.000)	(0.000)
AvgRatingRestaurant $_{j,t-1}$	1.213***	1.194***	1.194***
	(0.022)	(0.021)	(0.021)
AvgVariRestaurant $_{j,t-1}$	0.632***	0.704***	0.704***
	(0.026)	(0.028)	(0.028)
Log#CumReviews $_{j,t-1}$	1.740***	1.590***	1.589***
	(0.014)	(0.014)	(0.014)
Promoted $_{j,t-1}$	2.911***	2.724***	2.727***

	(0.431)	(0.404)	(0.405)
Claimed $_{j,t-1}$	1.103***	1.113***	1.113***
	(0.021)	(0.021)	(0.021)
Price $_{j}$	1.246***	1.260***	1.260***
	3.742***	3.717***	3.717***
Constant	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Month & restaurant category dummies	included	included	included
N	7,635,071	7,635,071	7,635,071

DV = whether user *i* reviews restaurant *j* in period *t* ($Review_{ijt}$). The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001.

5. Robustness Checks on Review Quality

5.1. Friend Contributions and Review Length

Past research has used the textual length of reviews as another proxy for review quality (Burtch et al. 2018; Pan and Zhang 2011), although it can be argued that review length is more indicative of effort. Still, we used review length as a robustness check. If a friend contribution motivates users to write better quality reviews, we expect the resulting reviews to be longer. To test this idea, we replaced votes with review length and re-estimated our review-quality model. Our results are shown in Table A6 (M1 and M2). Consistent with the vote-based measures of quality, *CurFrndReviews* has a positive effect on review length, which is in line with our main findings on review quality.

Table A6. Two Robustness Checks on Review Quality

	Review Length (DV = *LogLength*)		**Lagged Friend Reviews (DV = *LogCombinedVotes*)**
Independent Variables	**M1**	**M2**	**M3**
	Coefficient	Coefficient	Coefficient
	(SE)	(SE)	(SE)
CurFrndReviews $_{i,j,t-1}$	-	0.086**	0.088+
	-	(0.031)	(0.050)
CurFrndReviews $_{i,j,t-2}$	-	-	0.093
	-	-	(0.066)
NewReviews $_{j,t-1}$	-	0.005*	0.008*
	-	(0.003)	(0.003)
ReviewAge $_{i,j,t}$			-0.0006
			(0.0008)
Log-Likelihood	-14761.29	-14753.79	-17873.17
Adjusted R-squared	0.542	0.542	0.460
N	18,387	18,387	18,387

The subscript *t* in the variable names indicates the period in which the review event occurred. Control variables were the same as the vote-based analysis but omitted for brevity. The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

5.2. Effect of Older Friend Reviews

Similar to our analysis of review quantity, we also checked whether our result was robust when we included older friend reviews. Specifically, we added friend reviews in period *t-2* ($CurFrndReviews_{t-2}$) to our main model. Our results (Table A6, last column) show that *CurFrndReviews* in period *t-2* is not significant, suggesting that friend reviews in the last period, but not older ones, affect the quality of review contributed by the focal user. The coefficient of last-period friend reviews is marginally significant, suggesting that our main result on review quality still holds.

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