Socially Nudged: A Quasi-Experimental Study of Friends' Social Influence in Online Product Ratings

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Abstract

Social-networking functions are increasingly embedded in online rating systems. These functions alter the rating context in which consumer ratings are generated. In this paper, we empirically investigate online friends' social influence in online book ratings. Our quasi-experiment research design exploits the temporal sequence of social-networking events and ratings and offers a new method for identifying social influence while accounting for the homophily effect. We find rating similarity between friends is significantly higher after the formation of the friend relationships, indicating that with social-networking functions, online rating contributors are socially nudged when giving their ratings. Additional exploration of contingent factors suggests that social influence is stronger for older books and users who have smaller networks, and relatively more recent and extremely negative ratings cast more salient influence. Our study suggests that friends' social influence is an important consideration when introducing social-networking functions to online rating systems.

1 Introduction

Online product ratings often play a useful role in informing consumers when they are making purchasing decisions. The value of an online rating system lies in the effectiveness in soliciting truthful expressions of private evaluations from consumers of the products, which depends crucially on the rating context in which ratings are generated.[1] In this study, we examine the generation of online ratings from the perspective of social interactions between online reviewers. We are interested in understanding how social-networking function creates a rating context, a social choice architecture, in which users are constantly socially nudged in rating decisions (Thaler and Sunstein 2008). We empirically identify a response of users' ratings to their friends' ratings. In other words, social-networking function alters the rating context and online ratings are socially nudged. While social nudge can arise from both observational learning and peer pressure, given that the friends' ratings are not necessarily more accurate, deviations in users' ratings from their private information signals could undermine the usefulness of online rating systems. As more and more online rating websites integrate social-networking functions into their existing services, social nudge in online ratings is likely to have increasingly significant consequences (Salganik et al. 2006).

This paper examines friends' social influence in online book ratings using data from a large social network-based online rating website. While theoretical discussion about social influence has been abundant, empirically identifying and evaluating social influence between friends using observational data has been challenging due to empirical difficulties. In this study, we propose an empirical strategy to identify social influence in online ratings when there is a confounding homophily effect. This methodology is applicable to different online social networking contexts. Our identification strategy hinges on the ability to observe the time when a pair of users becomes friends and the time when they leave ratings for the same book before and after they become friends. By

[1] Rating context in this study refers to the virtual environment surrounding a user (reviewer) and the information therein.

examining the similarity in ratings before and after people become friends, we are able to estimate the direction and magnitude of social influence in ratings. One potential concern about the design is that the timing when people become friends was not manipulated. We conduct various robustness checks to ensure the validity of the design and rule out alternative explanations.

Our results suggest that, on top of taste similarity among friends (i.e., the homophily effect), users' earlier ratings exert social influence on their friends' later ratings. On average, rating similarity between online friends is about 1.9 times higher after they become friends. Extending the research design, we also examine a few contingent factors. This analysis suggests that those who have fewer friends are more easily influenced. The influence is more salient for older books. More recent and extremely negative ratings cast stronger impacts.

This study contributes to the literature in several ways. First, we contribute to the online word-of-mouth (WOM) literature by studying the impact of social context on the generation of ratings. WOM studies typically assume that consumers' ratings are based on their own opinions formed after the consumption. We point out that the rating context matters and user ratings are socially nudged by their online friends' opinions. Social nudge is introduced by the implementation of social-networking features in online WOM systems. The designers and users of social network-based online rating systems should be aware that although such systems might benefit from social-networking features in attracting users and improving their stickiness, social nudge as a result of interactions among friends may prevent users from giving independent evaluation of products.

Second, we contribute to the literature on social influence by proposing an innovative quasi-experimental design that identify social influence between online friends on top of the homophily effect (McPherson et al. 2001). Our research design exploits the temporal sequence of social-networking activities and rating events and offers an easy-to-implement way to derive causal interpretation from observational data. It explicitly takes care of endogenous friend relationship formation and the homophily effect. Unlike other empirical methods proposed to identify social influence that depends either on experimental manipulation or complex empirical assumptions, our method can be easily replicated in other contexts and scales well for big observational social-networking data sets.

Third, we contribute to the social contagion literature by empirically study friends' social influences in post-adoption opinion reporting. Previously, social influence is usually identified on the basis of an act of consumption or adoption. Insights obtained from studies of social influence in adoption cannot be easily applied to understanding post-adoption social influence in reporting, because the mechanisms through which the social influences take place in adoption and opinion reporting are likely to be different. To understand the social influence mechanisms, we investigate contingent factors that might moderate the identified social influence. These additional results serve both as a robustness check of the proposed methodology and as a starting point for managers and system designers to assess the managerial and strategic implications of social-networking features in online rating systems.

The rest of the paper is organized as follows. Section 2 introduces the background and reviews the literature. In Section 3, we discuss our research design. Section 4 introduces our empirical research context and measures. In Section 5, we present and discuss the results. Section 6 discusses the robustness checks and additional analyses including exploration of contingencies in social influence. Section 7 concludes.

2 Background and Literature Review

Recent years have witnessed rapid penetration of social media and social networks in various online applications. According to a study by Nielsen, Internet users spent 22.7% of their time on the Internet engaged in social media, up from 15.8 percent just a year ago (43 percent increase).[2] According to Pew Research Center, the percentage of American adults using online social-networking sites has reached 73% in 2013.[3] The dramatic development of these sites is attributable to their online social-networking features that enable individuals to follow each other's activities and to make online friends.

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[2] http://www.nielsen.com/us/en/newswire/2010/what-americans-do-online-social-media-and-games-dominate-activity.html, accessed in February 2014.

[3] http://www.pewinternet.org/2013/12/30/social-media-update-2013/, accessed in February 2014.

Attracted by the benefits of rapid viral growth and fewer fraudulent ratings, popular online rating sites are quick to embed social-networking features. Yelp (www.yelp.com), Rottentomatoes (www.tottentomatoes.com) and TripAdvisor (www.tripadvisor.com), for example, encourage users to invite friends to join the network and display friends' reviews and ratings in more prominent positions. The social-networking features make Yelp one of the biggest hits among the fastest-growing online rating services.[4]

This study examines the change in individuals' WOM reporting when they have access to their friends' ratings. Our research is broadly related to two streams of prior studies. First, we contribute to the online WOM literature by introducing a social nudge from friends. Second, we propose a quasi-experimental design to evaluate social influence.

2.1 Studies on Online Product Ratings and Reporting Biases

Online WOM is probably the earliest form of user-generated content (UGC). Individual consumers contribute to and benefit from Internet UGC applications such as online discussion boards (Antweiler and Frank 2004), Usenet groups (Godes and Mayzlin 2004), online exchange platforms (Resnick and Zeckhauser 2002), Wikipedia (Zhang and Zhu 2011), YouTube (Susarla et al. 2012; Yoganarasimhan 2012), and online movie/game/book rating systems (e.g. Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Liu 2006; Zhu and Zhang 2010). From a consumer's perspective, online ratings can significantly reduce the risk associated with the uncertainty of purchasing experience goods (Bolton et al. 2004; Pavlou and Gefen 2004). From a seller's point of view, such ratings are a valuable information channel and can be a useful marketing tool. Previous studies show the sales impact of various aspects of online WOM (Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Dellarocas et al. 2007; Duan et al. 2008; Godes and Mayzlin 2004; Liu 2006). As a result, firms are attentive and respond strategically to online ratings (Chen and Xie 2005; Dellarocas 2006; Hu et al. 2011).

The value of online rating systems lie in the quality of information they deliver, which depends on the underlying mechanisms of rating generation. Dellarocas (2006) argues

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[4] http://usatoday30.usatoday.com/money/industries/technology/2007-06-12-yelp_N.htm, accessed in February 2014.

that although consumer ratings may still be informative when firms can manipulate online ratings, ratings generated under this mechanism can result in a social welfare loss.

A number of recent papers examine the generation of online ratings and its consequences. The literature suggests that online ratings can be biased owing to the self-selection in user reporting. Li and Hitt (2008) develop a model to explain the dynamic pattern of product ratings as a result of consumers' self-selecting into early and late adopters. They empirically document that even with truthful reporting of perceived quality, early and later ratings should not be interpreted in the same way. Under certain conditions, this self-selection behavior can cause systematic bias in reviews posted in the early periods. Dellarocas et al. (2007) and Godes and Silva (2011) also report similar downward trend in product ratings. Hu et al. (2007) identify two sources of self-selection bias. First, there is an acquisition bias; that is, only consumers with a favorable disposition toward a product will buy it, thus creating a bias toward more positive reviews. Second, since consumers who are greatly satisfied or dissatisfied are more likely to report ratings, there is an under-reporting bias. Dellarocas and Wood (2008) find that reporting bias arises when one's propensity to report a privately observed outcome to an online reputation system is conditioned on the type of outcome. Selective under-reporting thus distorts the distribution of publicly reported ratings and renders judgments that are based solely on such ratings erroneous.

Wu and Huberman (2008) study the dynamic aspects of online opinion formation and find that exposure to previous opinions leads reviewers into a trend-following process of posting increasingly extreme ratings. Similarly, the empirical model of Moe and Trusov (2011) suggests that later ratings can be affected by earlier public ratings. Moe et al. (2011) explain the cause of reporting bias by a selection effect and an adjustment effect. Schlosser (2005) experimentally demonstrates a negativity bias in ratings when social concerns about self-presentation (appearing more intelligent and competent) are triggered.

Similar influence in opinion expression has been documented in marketing research long before the existence of online ratings. Cohen and Golden (1972) let subjects evaluate a brand of coffee under four different conditions with respect to information exposure and visibility expectation. They conclude that exposure to others' evaluations significantly influences subjects' ratings. In another study, Burnkrant and Cousineau (1975) find that information about prior evaluations significantly influence the ratings given by subjects.

Different from the existing literature that focuses on self-selection, intentional distortion, and the impacts of public rating information, we study the impacts of online friend relationship on product ratings. There are generally two mechanisms through which information about friends' ratings casts influence on a focal user's rating behavior, namely, informational influences and normative influences (Burnkrant and Cousineau 1975; Deutsch and Gerard 1955), which are also referred to in the literature as observational learning and peer pressure (e.g. Cai et al. 2009; Mas and Moretti 2009; Moretti 2011; Zhang 2010). Observational learning refers to the fact that friends' ratings convey new information about the product being reviewed that a user could rely on to update his evaluation. Peer pressure, on the other hand, refers to the tendency of a user conforming to friends' ratings motivated by positive identification with friends and to maintain close social connections. In either case, the social network connections and prior friends' ratings create a social context in which a user expresses his evaluations. This context is likely to have a significant impact on the ratings being produced. It is important to identify and acknowledge the impact of friend influence in online ratings considering that online review systems are increasingly dependent on embedded social networks and people have adapted to using online social networks to maintain close social connections.

In a related study, Lee et al. (2011) studiy the generation of online ratings from the social learning perspective and considers online friends' ratings as a source of learning. Their finding suggests that herding is present in online ratings, but public (non-friends') ratings exert higher influence than friend ratings. Different from their work which focuses on observational learning in the movie-rating context, we study the impact of friend relationship formation and social influence in rating behavior. More importantly, we propose an easy-to-implement research design to identify social influence between online friends. Our framework explicitly takes care of endogenous friend relationship formation and the homophily effect.

2.2 Studies on Social Networks and Identification of Social Influence

A large number of studies in social psychology demonstrate that people behave very differently when they are under social influences (e.g. Cialdini and Goldstein 2004). Research on communication networks, innovation diffusion, and opinion leadership has long recognized that consumers are influenced by others (e.g. Van den Bulte and Lilien 2001; Iyengar et al. 2011). There can be multiple mechanisms through which friends' ratings influence a focal user's rating. When individual buyers and reviewers leave online ratings, the presence of an online social network creates a social context that can exert social pressure on these reviewers. Under the influence of such pressures, the ratings' accuracy in reflecting a user's initial evaluation could be considerably undermined. The pressures of both conformity and social identification imply that friends' ratings may influence a focal user's rating (Burnkrant and Cousineau 1975; Cialdini and Trost 1998; Cialdini and Goldstein 2004). Some products or services (e.g., dietary supplements, exotic restaurants, and expert services such as medical procedures and automobile repairs), which are often referred to as credence goods, have the feature that consumers may have difficulty evaluating their quality even after consumption (see Dulleck and Kerschbamer 2006). For these goods, a focal user's rating may be influenced when he attempts to infer/learn the goods' quality from his friends' ratings in addition to the social pressures for conformity.

Much of the literature on social influence examines product and innovation adoption under uncertainty (e.g., Aral et al. 2009; Cai et al. 2009; Iyengar et al. 2011). Different from these studies that focus on adoption, our paper examines post-adoption opinion reporting. When consumers face pre-adoption uncertainty in products, herding (following others' actions without utilizing their own private information) can be a viable equilibrium strategy as a result of observational learning (Banerjee 1992; Bikhchandani et al. 1992). Insights obtained from studies of social influence in adoption, however, cannot be easily generalized to understand friends' social influence in post-adoption reporting, because the mechanisms through which social influences take place in adoption and opinion reporting are likely to be different.

Identifying friends' social influence in ratings is challenging because one cannot simply use the strong correlation in friends' ratings as an evidence of their influencing each other. Similarity in ratings can also result from similarity in friends' tastes (the homophily effect), or equivalently, the endogenous formation of friend relationships (Lazarsfeld and Merton 1954; McPherson et al. 2001). Homophily refers to the phenomenon that socially proximate individuals also tend to be similar with respect to their individual-level characteristics. Thus, similarities in their behavior may be driven by similarities in individual-level characteristics that are often unobserved, which results in the friends' behavior being endogenous. Distinguishing social influence from homophily and other confounding factors has been a well-known empirical challenge. Manski (1993) distinguishes and categorizes these challenges into the reflection problem, contextual interactions, and correlated effects. It is important to separate the effect of homophily from the effect arising out of social influence in our context, because these two effects have very different strategic implications for managers. If homophily is the only force behind the similarity in ratings given by friends, then managers should not be concerned about the high correlation between friends' ratings. If, instead, it is social influence that induces later reviewers to give ratings conditional on their friends' earlier ratings, then the rating-score trajectory will be path-dependent and whoever leaves the first rating will influence his friends' future ratings.

Various solutions have been proposed for distinguishing the effect of social influence from that of other relevant factors (Brock and Durlauf 2001; Soetevent 2006). The ideal method would entail conducting randomized experiments, by assigning individuals into different groups with different treatment conditions and examining the effect of social influence. Such randomized experiments are typically very costly to conduct because manipulation of social ties can be challenging. Field- and quasi-experiments are valid alternatives. Sacerdote (2001) examines peer influence on academic performance with a randomized sample of college students (see also Foster 2006). In their study of productivity spillover, Mas and Moretti (2009) leverage the quasi-random arrangement of working shifts. In a study of retirement plan enrollment, Duflo and Saez (2003) randomly vary the level of social interactions among potential participants and infer the impact of social interaction from the identified spillover effects. A limitation of these studies is that social interactions and social ties in the research context are often not directly observed and measured. In our study, the complete history of the social network's development is recorded, making it easier for us to measure the social relationships among users. Online randomized field experiments have also been conducted to identify social influence between online friends in product adoption (Aral and Walker 2011, 2012; Muchnik et al. 2013). These studies offer strong evidence of social influence between online friends. However, randomized experiments are costly to replicate. The method proposed in this paper is purely based on observed social relationship that are readily available to site managers.

A second approach relies on econometric manipulations, such as adding fixed effects and explicitly modeling the selection process. Identification can leverage the panel-data structure of social influences over time (Brock and Durlauf 2001) or the structure of network interactions (Bramoullé et al. 2009). Stochastic actor-based modeling approach has been lately proposed to model the coevolution of social networks and behavior (Lewis 2011; Snijders et al. 2006; Steglich et al. 2010). To compensate for the lack of empirical control and observations, these models tend to have strict requirements for the identification conditions (e.g. Angrist and Pischke 2010; Bollen and Pearl 2013; Summers 1991). In contrast, our identification does not require such strong modeling assumptions.

Social-interaction effects can also be estimated by exploiting natural instrumental variables or exogenous shocks (e.g. Brown et al. 2008; Conley and Udry 2010; Tucker 2008). Researchers engaging in this type of research leverage the richness of data to find creative ways of identification.

In our quasi-experimental design, we exploit the ratings' visibility and the dynamic feature of the social network to eliminate the homophily effect and identify social influence in friends' ratings.[5] Our empirical results confirm the existence of the homophily effect and reveal that the generation of online ratings is subject to friends'

[5] Parallel to this paper, a similar approach has been adopted to examine the similarity in the editing behavior of Wikipedia users (Crandall et al. 2008).

influence. Our approach is easy to implement in alternative social-network environments, especially in online social networks that feature large social groups and volumenous user activities. It offers a way to examine large-scale social interactions in contexts where implementing a full-scale randomized experimental design is infeasible.

3 Research Design

3.1 Identification of Social Influence – A Quasi-Experimental Design

Our estimation strategy builds up on a response function of focal user i's rating for book j, or $Rating_{ij}$, on i's friends' average rating of the same book, $AvgFrdRating_{ij}$, controlling for other user-book-specific factors at the time of the focal user's rating, X_{ij}:

$$Rating_{ij} = f\left(AvgFrdRating_{ij}, X_{ij}\right).$$

For $AvgFrdRating_{ij}$, we consider only the ratings for book j left by the friends of user i before the focal user i's rating (for book j). An important concern here is that since friend relationships are endogenously formed, the correlation between a focal user's rating and his friends' average rating may not be the result of social influence but a consequence of their sharing similar tastes. Similarity in tastes, or the homophily effect, confounds the social-influence interpretation of the response function. To tease out social influence from the homophily effect, an ideal experimental environment would require randomly picking subjects, manipulating the visibility of friends' previous ratings, and then examining whether the subject's action differs under various visibility treatment conditions. However, such experiments are hard to conduct on a large scale in functioning social networks. To achieve similar rigor in identification while taking advantage of naturally available observational data, we can rely on a quasi-experimental design (Campbell and Stanley 1963). As we show below, with certain testable assumptions, quasi-randomization over rating visibility can be achieved based on the timing of both ratings and friend relationship formation.

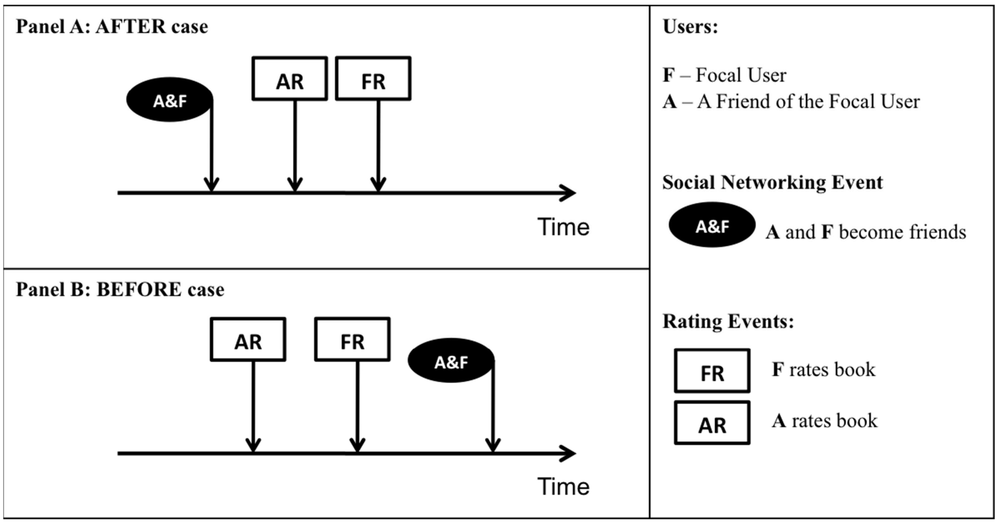

Figure 1: Illustration of Relative Timing of Ratings and Social-Networking Events

Figure 1 depicts the (relative) timing of three events that we leverage in the empirical framework. The three events occur (1) when the focal user leaves a rating for product X (FR), (2) when the focal user's friend A leaves a rating for product X (AR), and (3) when the focal user and user A form an online friend relationship (A&F). Panel A shows the AFTER case, in which the focal user's rating takes place *after* the friend relationship forms. In Panel B, the focal user leaves the rating *before* he becomes a friend with user A. Although the permutation of the timing of the three events can yield six cases, in our framework we need to consider only two. First of all, three cases are eliminated because we require that AR must be earlier than FR, to ensure the direction of social influence. Because we consider every user as a focal user once, this requirement does not prevent us from using all available data. In other words, the permutation of AR and FR is not relevant. On a second dimension, we do not differentiate with respect to the sequence of AR and A&F. The rationale behind this choice is that in either case, at the time of the focal rating, the focal user can observe user A's rating. Therefore, given that user A rates a product before the focal user (i.e., AR before FR), we can focus only on the relative timing of A&F and FR. As such, our empirical identification of social influence in user ratings is based on a comparison of the cases illustrated in Panels A and B. In the AFTER case (Panel A), the focal user and user A are already friends when the focal user makes his rating. In the BEFORE case (Panel B), the focal user is not yet a friend with user A when he leaves the rating. User A's rating is thus salient as a friend's rating in the AFTER case in Panel A, but not in Panel B. If the correlation between the two users' ratings is stronger in the AFTER case, we would have evidence to support that there is a social influence in ratings as a result of the online friend relationship.[6] In other words, to separate social influence from the confounding homophily effect, we examine similarity in ratings before and after the friend relationship. Using the BEFORE case as a control helps us establish benchmarks of inherent rating similarity between friends.

Each focal user's friends are defined according to their relationship by the end of the observation period (the complete friend network). For friends of a focal user who have rated the same book, we define a dummy variable to indicate whether the focal user's rating takes place before they become friends ($After_{ij} = 0$, Panel B in Figure 1) or after they become friends ($After_{ij} = 1$, Panel A in Figure 1). The variable $After_{ij}$ therefore indicates whether, at the time of the focal user's rating of book j, the rating of the same book by his friend (happened before i's rating of book j) is salient to the focal user as a friend's rating or not. Since visibility of an influencers' behavior is the single most important pre-condition for social influence to take place (Marsden and Friedkin 1993; Mas and Moretti 2009), we examine the parameter estimate of the interaction between $After_{ij}$ and $AvgFrdRating_{ij}$ to identify the social influence. Without social influence, the similarity in friends' tastes should remain the same no matter the focal user can view his friends' ratings or not; we then would expect to see no effect of $After_{ij}$ on the rating similarity (the relationship between $Rating_{ij}$ and $AvgFrdRating_{ij}$). If there is social influence, we should identify a significant interaction effect between $After_{ij}$ and $AvgFrdRating_{ij}$. Following this reasoning, we can include the treatment effect of $After_{ij}$ in the response function as:

$$Rating_{ij} = f\left(AvgFrdRating_{ij}, After_{ij}, After_{ij} \times AvgFrdRating_{ij}, X_{ij}\right),$$

where $After_{ij}$ indicates whether the focal user i has formed friend relationships with

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[6] Focal user ratings with no previous friends' ratings are therefore excluded from the current research design.

those for whom we calculate $AvgFrdRating_{ij}$ when he rates book j.

Based on our research design, the traditional linear-in-mean social interaction model (Brock and Durlauf 2001) that allows for variations across books and users with other control variables can be written as the following:

$$Rating_{ij} = \alpha + \beta_1 AvgFrdRating_{ij} + \beta_2 After_{ij} + \beta_3 AvgFrdRating_{ij} \times After_{ij} + X_{ij}\gamma + u_i + \nu_j + \varepsilon_{ij}. \quad (1)$$

Since $After_{ij}$ is a dummy variable, to calculate a meaningful measure of $AvgFrdRating_{ij}$, we require that these friend ratings are either all from the AFTER period or all from the BEFORE period, but not from both. In Figure 2, Panel A shows the case when the focal rating (FR) is after the time when both A and B become friends (A&F and B&F) with the focal user (the AFTER case). Panel B shows that FR is before both A&F and B&F. In these two cases, $After_{ij}$ is well defined.

The situation becomes more complicated if friend relationship formation can occur both before and after the focal rating. Panel C of Figure 2 demonstrates such a case, in which A&F comes before FR, but B&F comes after FR.[7] We separately analyze this situation to offer corroborating evidence in an extension in Section 6.4.

Combining the cases in Panel A and B of Figure 2, $After_{ij}$ is well defined and can be interpreted as the treatment effect. Since a significant increase in rating similarity following users' becoming friends cannot be explained by the homophily effect, the interaction term between the time dummy and average friends' rating ($After_{ij}$*$AvgFrdRating_{ij}$) teases the social influence effect out of the homophily effect.

[7] Note that it is required that the focal users rating is given after the friends' ratings because an earlier rater's rating should not be influenced by a later rater's rating.

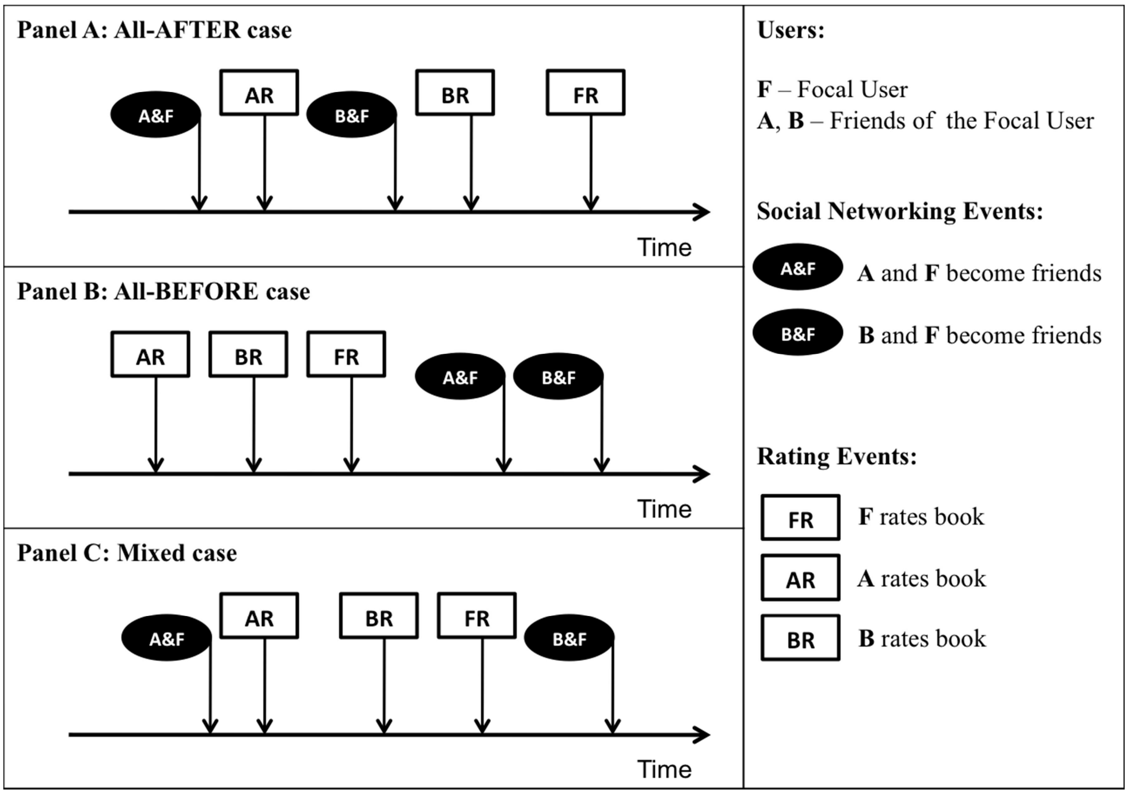

Figure 2: Illustration of Relative Timing of Ratings and Social-Networking Events with Two Friends

3.2 Discussion of the Identification Strategy

In the proposed quasi-experimental research design, there are several things out of our control: first, the pair of friends cannot be randomized (endogenous friend relationship); second, the time when two users become friends cannot be manipulated (endogenous timing of friend relationship formation); and finally, the order of giving ratings is self-selected (endogenous timing of ratings). We next explain how these concerns are addressed in this study.

Endogenous Friend Relationship

Endogenous friend relationship refers to the fact that people select their friends based on commonality. In observational studies, we have no control over why they select certain people as friends but not others. Endogenous friend relationship can bring identification challenges because of the homophily effect and when the objective of a study is related to examining how friend relationship differs from other types of relationships.

In our study, this is not a concern. First, endogenous friend relationship is explicitly considered in the research design and we would like to examine how social influence may exist on top of homophily. In other words, naturally formed friend ties are desirable in the proposed research design to bring the similarity in tastes. Second, our research focuses on pairs of users who eventually become online friends. The comparisons are not with respect to whether people make friends or not. Rather, all our subjects use the friend function to form online friend relationships within the observation period. To this end, self-selection to become friends is irrelevant to our research design since it involves no comparison between friends and strangers. Third, while people may develop different types of friend relationships that have different level of influences, in the baseline model, we are interested in identifying the average treatment effect across all subjects in the sample. In the extension, we explore variations in friend relationships.

Our research design leverages on the relative order of friend relationship formation and ratings to create treatment and control groups. As with all quasi-experimental designs, it is crucial to assess whether the treatment can be considered reasonably random. Consequently, it is important to discuss the validity of the quasi-experimental design in terms of the randomness of the timing of these events. We examine these conditions next.

Endogenous Timing of Friend Relationship Formation

Endogenous timing of friend relationship formation refers to the problem that people not only self-select to be friends with certain people (the previous concern), they also self-select the time when they become friends. This is the most significant challenge to our design. A crucial assumption to be satisfied is that the temporal sequence of users becoming online friends with each other is not systematically related to the similarity between them. If the earlier friend relationships indeed exhibit higher similarity than later ones, due to the cumulative nature of online ratings, a temporal sampling bias that are common to quasi-experimental designs would arise. In this case, we would sample more shared ratings from similar friends than from dissimilar friend in the AFTER case because similar friends tend to form friend relationships earlier than dissimilar friends. If this happens, social influence identified by the $After_{ij}$ treatment would be contaminated and constitute an overestimate of the actual social influence in ratings.

To address this concern, we need to rule out the possibility that earlier friends are more similar than later friends. We carry out a few robustness checks. First, we take into consideration the tenure of friend relationship between users. We demonstrate with two methods that earlier friends are not more similar to focal users than later friends. Second, we consider an additional analysis at the friend-pair level and examine rating similarity between the same pair of friends. That is, for two users who eventually become friends, we show that the rating difference between them reduces after they are allowed to see each other's ratings. Since this estimation is on the friend-pair level, the timing of friend relationship formation could be further controlled by friend-pair fixed effect. Finally, we demonstrate that a pair of friends do not naturally become more similar over time. Based on the dyad-level analysis, we show that (1) people in a friend pair do not become more similar before the introduction of the social-networking function, and (2) introduction of the social-networking function alone does not trigger higher similarity in friend pairs: only when two users becomes friends (thus can view each other's ratings), social influence takes place. These additional analyses are reported in Section 6.

Endogenous Timing of Ratings

In a perfectly randomized experiment, subjects' roles are selected before the experiment. Subjects in the treatment group would see their friends' earlier ratings and those in the control group would not see their friends' ratings. In our design, we cannot pick subjects' roles up front. Focal users' ratings (in both the control group and the treatment group) are always the later (relative to friends') ratings by the users.

This self-selected rating order does not affect our design and result. First, our empirical test hinges on whether friends' ratings are visible or not. Even if later ratings are systematically more similar or different from earlier ratings, we should not find significant difference before and after when friends' ratings are visible if not for social influence. Second, it is possible for some users to change their habits after the implementation of the friend function so that they wait longer in order to see their friends' ratings before giving their own ratings, but this supports our main argument that once the social-networking functions are implemented, social influence plays a bigger role in people's online ratings. In our robustness checks, we examine whether friendship function alters users' responses to friends' ratings.

Social Influence before Friend Relationship

In social-networking sites, users may keep track of ratings by other users before forming online friend relationships since the formation of friend relationships requires mutual recognition. This results in users being influenced by their friends even before friend relationships are formed. While our research design leverages on the observation of friend relationship formation, we make no assumption that social influence between online friends only exists after the friend relationships are formed. If there is social influence even before friend relationship formation, our estimated social influence would underestimate the real influence.

4 Research Context, Data and Measures

4.1 Research Context

To implement the above research design and test the significance of social influence in online ratings, we obtained data from one of the most influential online rating website for books, movies, and music in China. Established in 2005, the site has more than 8 million registered users and attracts more than 10 million pageviews per day. These pageviews can be from either registered or unregistered users. Registered users can leave ratings and write reviews about items that they have consumed and gradually form an online profile that serves as the foundation of social-networking activities on the site, whereas unregistered users mainly browse the site to acquire information about books, movies, and music.[8]

Through the "search" and "browse" functions, users can rate items, which then form a personal collection of books, movies, and music for each user. The site's collaborative-filtering algorithm uses information from user collections to suggest new items and potential social connections. When reviewing an item, a user can write down his opinion and choose a star rating from one to five. All ratings and reviews are public.

[8] In the rest of the paper, "user" refers to registered users, as only registered users can have online friends and rate items.

Figure 1 shows screen shoots of a book page (Figure 3-A) and the user interface for rating (Figure 3-B).

A. Book Page

B. Rating Dialog Box

C. User Profile Page

D. Friend Updates

Figure 3. Screen Shots of Book Page, Rating Dialog Box, User Profile Page, and Friend Updates

The site also shows friends' activities conspicuously. Friend requests can be easily initiated with a click of a button on users' profile pages (Figure 3-C). If a targeted user agrees to the friend request, an online friend relationship will be formed. Once two users form a friend relationship, each will be updated about the other's activities including ratings (Figure 3-D).[9] This mechanism makes the friends' ratings distinctively salient

[9] The social updates only show information from direct friends. While a user can explore the

from ratings by other users that are presented in aggregation on the book page (Figure 3-A). Salient information of friends' ratings is a critical condition for social influence to take place. On the one hand, the salience of friend's rating-information feed enable a user to be aware about the expressed opinions of his friends. On the other hand, the users are also aware of the fact that their expressed opinions will be easily accessible to their friends.

A user can communicate with other users on the site in various online activities. For example, they can search for users who collect similar items; read others' reviews; participate in discussion forums and online groups; and be notified about new friend relationships of their current friends. The site promotes friend relationships by collecting user preference data and provides users with information about their common interest with other users. If a user visits another user's profile page, the site will automatically show the items that they both liked. While being the most influential user review sites for cultural products, the site is strategically positioned as a social-networking site and does not feature functions that recognize users' contributions as reviewers as much as other review sites (for example, Yelp gives badges to differentiate reviewers). Only users' collections and activities are shown on user profile pages (Figure 3-C). There is no salient information that vertically differentiates users. Decisions to initiate friend relationships are mostly based on common interests and on-site social interactions. The site also provides a messaging function for users to communicate.

There are various reasons that a user wants to befriend other users on the site. In general, prior social psychology research suggests that people makes friends with those who share common characteristics, high level of intimacy and identity. The purpose to form friend relationship includes developing intimacy (based on common characteristics) and obtaining resources and social support (Rule et al. 1985). Friend relationship bears mutual recognition and psychological intimacy. It carries the intention to build and maintain friend relationships by meeting others' expectations and needs. The motivation

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friend lists of his friends (second-degree friends), to get information about the activities of a friend's friend, he needs to go to that user's profile page. The site does not offer a function to silent a friend. The only way to stop receiving updates of a friend is by un-friending the user.

to build and maintain friend relationship makes people respond to friends with conformity and reciprocity to get social approval (Asch 1956; Cialdini and Trost 1998; Deutsch and Gerard 1955; Fishbein and Ajzen 1975, Levine 1980; Thibaut and Strickland 1956). Online friend relationships carry similar characteristics, motivations and functions. In our research context, users meet each other in online social interactions (ratings, reviews, and discussions), in which they discover common interests that cultivate online friend relationships. Once friend relationships form, users maintain and develop them by engaging with each other in online activities.

4.2 Data and Measures

We collect the data from the site's data server archive. It contains the entire history of user' ratings for items (including books, movies, and music). The complete dataset has about 50 million ratings for over a half-million items from about 890,000 users. We also observe the social network typology. The entire social network in our data set contains over 2 million links among 286,140 users. In this study, we focus on observations of book ratings from February to August 2008.

Based on this data set and our research design, we estimate the following linear-in-mean social interaction model (Brock and Durlauf 2001):

$$Rating_{ij} = \alpha + \beta_1 AvgFrdRating_{ij} + \beta_2 After_{ij} + \beta_3 AvgFrdRating_{ij} \times After_{ij} + X_{ij}\gamma + u_i + \nu_j + \varepsilon_{ij}.$$

In the model, the dependent variable is a focal user i's rating on book j, $Rating_{ij}$. For each observation, we search through the user's friend network (by the end of the observation period) and identify those friends who have rated the same title before and thus may have exerted an influence on him. This process yields a measure for focal user i's friends' average rating for book j, $AvgFrdRating_{ij}$.

As discussed in Section 3, our empirical identification relies on the relative timing of friend relationship formation and friend ratings. In the BEFORE case, $AvgFrdRating_{ij}$ is given before the friend relationships form while in the AFTER case $AvgFrdRating_{ij}$ is given after the friend relationships form. In Equation 1, $After_{ij}$ is a dummy variable that indicates whether the $AvgFrdRating_{ij}$ belongs to the BEFORE case ($After_{ij} = 0$) or the AFTER case ($After_{ij} = 1$). The interaction between $After_{ij}$ and $AvgFrdRating_{ij}$ (β_3) thus identifies the social influence.

From Figure 2, we know that it is possible to have $AvgFrdRating_{ij}$ coming from both the BEFORE period and the AFTER period when there are more than one friend who has rated the book. To clearly define $After_{ij}$, we require that friends' ratings for calculating $AvgFrdRating_{ij}$ are either all from the BEFORE cases or all from the AFTER cases. This process gives us a data set of 171,588 ratings, covering 20,480 book titles by 33,605 users.[10]

Control Variables

In Equation (1), we include various measures of rating, book and user characteristics as controls. We capture the decay of social influence with a variable that measures the days from friends' last rating to the time of the focal rating, $Recency_{ij}$. Smaller $Recency_{ij}$ indicate that friends' ratings are more recent.

In terms of book characteristics, we calculate book age ($BookAge_{ij}$), measured by the number of days from the time book j appeared in the dataset to the time of the focal rating, and rating intensity ($RatingIntensity_{ij}$), measured by the average number of ratings per day before the focal user's rating. To control for general opinions on each book, we also include the count, average, and variance of the ratings for book j of all users at the time of the focal rating ($NumRating_{ij}$, $AvgRating_{ij}$, and $VarRating_{ij}$). An average book in our data set gets a rating of 4.1 on a five-star scale. Before getting each focal rating, an average book has been on the site for about 829 days since its first rating and has received 2,894 user ratings. In addition to these covariates, we also introduce book-fixed effects to control for how book characteristics may affect the similarity between the focal rating and the focal user's friends' ratings.

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[10] Following the same logic of our research design, we use an alternative empirical model to study the case of Panel C of Figure 2 in Section 6.4.

As for the users, we control user experience, measured by the number of days from user i's first appearance in the dataset to the time of the focal rating ($UserAge_{ij}$), the number of friends that user i has ($NumFrd_{ij}$) and the number of books that user i has rated ($NumBook_{ij}$) by the time of the rating. On average, users in our data set have 17 friends. They have been using the system for 244 days, during which they rate 164 books.

Table 1: Variable Definitions and Summary Statistics

Variable Name	Definition	Summary Statistics Mean (Std. Dev.) Original	Logged
Rating Variables			
$Rating_{ij}$	Focal user i's rating for book j	4.111 (0.845)	1.388 (0.242)
$AvgFrdRating_{ij}$	Average rating for book j given by the focal user's friends before the focal rating	4.134 (0.810)	1.396 (0.233)
$After_{ij}$	A dummy variable that equals to 1 in cases where $AvgFrdRating_{ij}$ is from users who had become friends of the focal user (AFTER cases) and equals to 0 otherwise (BEFORE cases)	0.545 (0.498)	
$Recency_{ij}$	Days from friends' last rating to the time of the focal rating	191.1 (214.3)	4.426 (1.580)
Book Variables			
$BookAge_{ij}$	Days from book j's first appearance in the data set to the time of the focal rating	828.8 (342.1)	6.545 (0.763)
$RatingIntensity_{ij}$	Average number of ratings per day for book j before the focal rating	8.828 (15.30)	1.608 (1.150)
$AvgRating_{ij}$	Average rating (valence) for book j given by other users before the focal rating	4.088 (0.343)	1.404 (0.0878)
$NumRating_{ij}$	Volume of user ratings for book j before the focal rating	2894.4 (4339.7)	6.548 (2.126)
$VarRating_{ij}$	Variance of user ratings for book j before the focal rating	0.611 (0.205)	0.469 (0.125)
User Variables			
$NumFrd_{ij}$	Number of friends that focal user i has made before the focal rating	17.19 (38.46)	2.000 (1.294)
$UserAge_{ij}$	Days from focal user i's first appearance in the data set to the time of the focal rating	243.8 (272.6)	4.173 (2.258)
$NumBook_{ij}$	Number of ratings focal user i gave to other books before the focal rating	163.5 (423.6)	4.055 (1.510)
Number of Users		33,605	
Number of Books		20,480	
Number of Obs.		171,588	

Definitions, summary statistics, and the correlation matrix of variables are summarized in Tables 1 and 2.[11] We also calculate the variance inflation factors (VIFs) according to Equation 1. VIFs of all variables are lower than 3, indicating that the independent variables do not suffer from serious multi-collinearity issues (Kutner et al. 2004; Marquardt 1970).

Table 2: Correlation Table

	Variable	2	3	4	5	6	7	8	9	10	11
1	$Rating_{ij}$	0.229	*0.006*	0.032	-0.011	0.369	0.006	-0.224	-0.036	-0.063	-0.105
2	$AvgFrdRating_{ij}$		-0.017	*-0.002*	-0.043	0.419	-0.040	-0.259	0.008	0.006	-0.011
3	$Recency_{ij}$			0.301	-0.026	*-0.001*	0.120	0.016	-0.094	-0.006	-0.017
4	$BookAge_{ij}$				0.007	*0.006*	0.451	0.073	-0.112	-0.158	-0.129
5	$RatingIntensity_{ij}$					-0.076	0.835	0.259	-0.264	-0.225	-0.378
6	$AvgRating_{ij}$						-0.061	-0.577	0.034	0.039	0.030
7	$NumRating_{ij}$							0.289	-0.296	-0.275	-0.400
8	$VarRating_{ij}$								-0.102	-0.089	-0.130
9	$NumFrd_{ij}$									0.531	0.554
10	$UserAge_{ij}$										0.623
11	$NumBook_{ij}$										
	VIF	2.389	1.107	1.253	1.724	1.831	2.032	1.640	1.195	1.253	1.199

NOTE:

a. Correlations are displayed in *italic* font if p-value > 0.01.

b. VIFs are calculated based on the main model as expressed in Equation (1).

5 Results

5.1 Estimation Results

Estimation results for the linear-in-mean model are reported in Table 3. The results of the main model are reported in column (2) of Table 3. In the “naïve” model (1), we also estimate the parameters with all friends’ ratings pooled together without considering the relative timing of focal user’s ratings and the formation of friend relationships. In addition to observable user- and book- characteristics, we control for user- and book-fixed effects in both models. As expected, $AvgFrdRating_{ij}$ is significant and

[11] To alleviate the potential problem of non-normality in some variables, we conduct our analysis with continuous variables log-transformed. Our empirical results are robust and remain qualitatively the same with or without log-transformation.

positive, indicating friends' ratings are similar to each other. However, the similarity in focal users' ratings and their friends' ratings may be a result of both the homophily effect and the social influence effect. Consistent with previous studies on online WOM dynamics (Moe and Schweidel 2012), a focal user's rating is lower when (a) he is more experienced ($NumBook_{ij}$), and (b) the book has been intensively rated ($RatingIntensity_{ij}$).

Column (2) of Table 3 estimate our main model, in which we introduce the "treatment" variable, $After_{ij}$, and its interaction term with $AvgFrdRating_{ij}$. The positive and significant interaction term suggests that social influence from friends' ratings indeed exists. A back-of-the-envelope calculation suggests that, on average, rating similarity almost triples (increases by 190%) after users become friends.[12] The coefficient of $AvgFrdRating_{ij}$ is positive and significant, indicating that over 30 percent of the rating similarity identified in the naïve model comes from the homophily effect. Consistent with prior findings that people become more critical when they are more experienced, we also find that the focal users' ratings in the AFTER period are generally lower than in the BEFORE period. It is interesting to note that in model (2), after controlling for the book fixed effect, the average of previous public ratings ($AvgRating_{ij}$) appear to be negatively correlated with the focal user's rating. This is consistent with existing literature that individual raters exhibit a tendency of diverging from public ratings (Moe and Trusov 2011).

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[12] According to estimation results reported in column (2) of Table 3, the partial correlation between the focal users' ratings and previous friend's ratings, controlling for other covariates, is 0.0259 before the formation of friend relationship. The number is 0.0753 after friend relationship is formed, suggesting an increase of $\frac{0.0753}{0.0259} - 1 = 191\%$. Meanwhile, if we look at the simple correlation between the two (from column 1), the number is 0.2075 in the BEFORE cases and 0.2594 in the after cases, an increase of 25%.

Table 3: Friends' Social Influence in Online Product Ratings

	(1)	(2)
	DV: $Rating_{ij}$	
$AvgFrdRating_{ij}$	5.09e-02***	2.59e-02***
	(2.87e-03)	(3.88e-03)
$After_{ij}$		-3.13e-03*
		(1.80e-03)
$AvgFrdRating_{ij}$		4.94e-02***
$\times After_{ij}$		(5.16e-03)
<u>Controls:</u>		
$AvgRating_{ij}$	-7.45e-01***	-7.49e-01***
	(6.90e-02)	(6.90e-02)
$NumRating_{ij}$	-1.62e-02*	-1.62e-02*
	(9.39e-03)	(9.39e-03)
$VarRating_{ij}$	8.63e-02***	8.45e-02***
	(2.62e-02)	(2.62e-03)
$Recency_{ij}$	9.71e-04**	9.14e-04**
	(4.55e-04)	(4.65e-04)
$BookAge_{ij}$	-1.01e-02	-9.41e-03
	(1.07e-02)	(1.06e-02)
$RatingIntensity_{ij}$	-3.10e-02**	-3.11e-02**
	(1.30e-02)	(1.30e-02)
$NumFrd_{ij}$	8.17e-05	9.55e-04
	(1.29e-03)	(1.38e-03)
$UserAge_{ij}$	-1.35e-03	-1.28e-03
	(1.06e-03)	(1.06e-03)
$NumBook_{ij}$	-1.65e-02***	-1.66e-02***
	(1.15e-03)	(1.15e-03)
User-Fixed Effects	Yes	Yes
Book-Fixed Effects	Yes	Yes
Number of Users	33,605	33,605
Number of Books	20,480	20,480
Number of Obs.	171,588	171,588
Adjusted R^2	0.336	0.337

NOTES:

a. Model 1 (The Naïve Model) is a linear-in-mean model controlling user and book fixed effects. Model 2 (The Main Model) identifies social influence based on our empirical strategy controlling user and book fixed effects.

b. We use the dummy variable approach to control for fixed effects in the model. All continuous variables are log-transformed and centralized. Regression results based on original data values are qualitatively the same.

c. Standard Errors are reported in parentheses. Significance levels are displayed as *** p<0.01, ** p<0.05, *p<0.1.

6 Robustness Checks and Additional Analyses

In this section, we offer several robustness checks and discuss the validity of our main results. Additional analyses are also conducted to offer corroborating support to our main findings. First, due to the discrete nature of the rating variables and various ways to measure friends' similarity, we examine alternative model specifications using the same identification strategy. Second, we discuss how endogenous timing of friend relationship formation may affect our results by comparing earlier friends with later friends to rule out the alternative that rating similarity is related to friend relationship tenure. Third, we report a dyad-level analysis to examine rating similarity between each pair of friends. This analysis gives strong support to the robustness of our results. Our fourth extension makes use of the rating cases dropped from the main analysis when multiple friends' ratings come from both the BEOFRE and the AFTER periods (Panel C of Figure 2). In the fifth extension, we check whether unobserved systematic changes in how users respond to previous ratings may explain our results. Finally, we examine contingent factors that may moderate the social influence in online ratings.

6.1 Alternative Empirical Model Specifications

In order to assure the robustness of the findings derived from our research design, we test the model under different specifications. First, our results from previous sections are based on linear regression analysis. Considering the discrete nature of online ratings, we implement Ordered Logit models to reproduce our findings.[13] Second, following the traditional linear-in-mean model, we examine the relationship between focal users' ratings and their friends' ratings in our model to measure the impact of friends' social influence. It is interesting to see (1) whether the deviations of the focal users' ratings from public ratings are influenced by the deviations of friends' ratings from public ratings; (2) whether the absolute difference between focal users' ratings and their friends' ratings changes with the formation of online friend relationship.

[13] We thank an anonymous reviewer for suggesting this test.

Table 4: Robustness Check - Alternative Model Specification

	(1)	(2)	(3)	(4)
	DV: $Rating_{ij}$	DV: $Rating_{ij}$	DV: $(Rating_{ij} - AvgRating_{ij})$	DV: $\lvert Rating_{ij} - AvgFrdRating_{ij}$
$AvgFrdRating_{ij}$	1.51e-01***	1.57e-01***		
	(8.82e-03)	(9.83e-03)		
$After_{ij}$	-8.49e-02***	-9.82e-02***	-1.47e-02**	-2.99e-02***
	(1.04e-02)	(1.35e-02)	(6.22e-03)	(6.18e-03)
$AvgFrdRating_{ij} \times After_{ij}$	9.69e-02***	1.02e-01***		
	(1.15e-02)	(1.28e-02)		
$AvgFrdRating_{ij} - AvgRating_{ij}$			2.67e-02***	
			(4.07e-03)	
$(AvgFrdRating_{ij} - AvgRating_{ij}) \times After_{ij}$			4.54e-02***	
			(5.62e-03)	
Controls:				
$AvgRating_{ij}$	8.27e+00***	9.39e+00***		-3.90e-02
	(7.55e-02)	(8.56e-02)		(2.36e-01)
$NumRating_{ij}$	-1.19e-02*	9.35e-03	-1.67e-02	1.36e-02
	(6.94e-03)	(8.36e-03)	(3.23e-02)	(3.22e-02)
$VarRating_{ij}$	-1.87e-01***	-4.77e-01***	1.08e+00***	-3.42e-01***
	(5.01e-02)	(5.56e-02)	(8.31e-02)	(8.98e-02)
$Recency_{ij}$	-8.23e-04	6.44e-03*	3.36e-03**	7.64e-03***
	(3.07e-03)	(3.64e-03)	(1.57e-03)	(1.56e-03)
$BookAge_{ij}$	3.54e-02***	4.99e-02***	1.13e-02	-4.63e-04
	(1.07e-02)	(1.26e-02)	3.67e-02	(3.65e-02)
$RatingIntensity_{ij}$	-3.29e-02***	-5.69e-02***	-9.09e-02**	1.12e-01**
	(1.12e-02)	(1.32e-02)	4.50e-02	(4.47e-02)
$NumFrd_{ij}$	5.55e-02***	3.68e-02***	-6.30e-03	1.01e-02**
	(4.80e-03)	(7.59e-03)	(4.75e-03)	(4.73e-03)
$UserAge_{ij}$	-1.64e-02***	-2.84e-02***	-8.82e-03**	6.40e-03*
	(2.76e-03)	(4.73e-03)	(3.66e-03)	(3.64e-03)
$NumBook_{ij}$	-1.86e-01***	-1.86e-01***	-6.14e-02***	7.77e-03**
	(4.40e-03)	(6.90e-03)	(3.97e-03)	(3.95e-03)
Other Controls	No	User Random Effects	User and Book Fixed Effects	User and Book Fixed Effects
Number of Users	33,605	33,605	33,605	33,605
Number of Books	20,480	20,480	20,480	20,480
Number of Obs.	171,588	171,588	171,588	171,588
Adjusted R^2			0.242	0.090
Log Likelihood	-1.86e+06	-1.75e+06		

NOTES:

a. Models 1 & 2 report estimation results from the Ordered Logit Models.

b. Model 3 considers the rating deviations from public ratings. Specifically, we regress ($Rating_{ij}$– $AvgRating_{ij}$) on ($AvgFrdRating_{ij}$– $AvgRating_{ij}$) with control variables and user and book fixed effects.

c. Model 4 considers the change in the absolute difference between a focal user's ratings and his friends' ratings after the formation of friend relationship. Control variables and user and book fixed effects are included.

d. Standard Errors are reported in parentheses. Significance levels are displayed as *** p<0.01, ** p<0.05, *p<0.1.

Estimation results are reported in Table 4. Models 1 and 2 implement Ordered Logit estimation. The results suggest that the findings from our main model reported in Table 3 are robust to alternative model specifications.

Model 3 of Table 4 examines the relationship between focal users' rating deviations from public rating and their friends's ratings. The result shows that the influence is significant in terms of rating deviation. We also find that the deviation is more significant when the variance of public rating increases, when friends ratings are more recent, when the deviation is smaller, when the rating intensity is higher and when the focal users are more experienced (higher value of $UserAge_{ij}$ and $UserBook_{ij}$). To further corroborate our findings, we regress the absolute difference between the focal users' ratings and friends' ratings on the quasi-experimental treatment variable ($After_{ij}$). Consistent with our main analysis, we find a significant increase in rating similarity (as measured by smaller absolute rating differences) after the online friend relationships are formed. Rating similarity is higher when the variance of public ratings is higher. At the same time, rating similarity is lower when the intensity of rating is higher and when the users are more experienced.

Model estimations considered in Table 4 further corroborate our finding from the main model. Interestingly, it suggests that the strength of social influence in online ratings could vary across books and users. This result motivates additional exploration on the potential moderating effects (see Section 6.6).

6.2 Are Earlier Friends More Similar to the Focal User?

As discussed in Section 3.2, our research design relies on an assumption that the temporal sequence of two users becoming online friends is not related to the similarity between them. A natural concern is that it is possible for a user's earlier friends to be more similar to him compared to his later friends. If this is the case, the significant and positive interaction term in the main model may be attributed to a temporal sampling bias generated by the difference in similarity of friends added at different times (i.e., ratings in the AFTER period ($After_{ij} = 1$) are more likely to be from those earlier friends).

Table 5: Robustness Check – Tenure of Friend Relationship

	(1)	(2)
	DV: $RatingDiff_{ij}$	DV: $Rating_{ij}$
$FrdTenure_{ij}$	-1.69e-03	2.61e-03
	(1.41e-03)	(2.88e-03)
$AvgFrdRating_{ij}$		9.80e-02***
		(7.18e-03)
$AvgFrdRating_{ij} \times FrdTenure_{ij}$		-7.64e-04
		(1.99e-03)
Control Variables	Yes	Yes
User Fixed Effect	Yes	Yes
Number of Users	25,998	25,998
Number of Obs.	117,754	117,754
With-In R^2	0.000	0.191

NOTES:

a. We include all control variables considered in the main analysis. Coefficient estimations for these control variables are similar.

b. $RatingDiff_{ij} = Rating_{ij} - AvgFrdRating_{ij}$.

c. Standard Errors are reported in parentheses. Significance levels are displayed as *** p<0.01, ** p<0.05, *p<0.1.

To test whether this potential difference in similarity between earlier and later friends is a serious concern, we explicitly consider the tenure of friend relationship. The rationale behind this test is that if earlier friends are more similar to a focal user, we should observe that the focal user's ratings are more similar to the ratings of his older friends. We construct a subsample of the data used in our main analysis by considering friends' ratings only in the AFTER period. This way, each friend's rating can be associated with a measure of the friend relationship tenure between the friend and the focal user. For each $AvgFrdRating_{ij}$ in this sample, we also have a measure of the average friend relationship tenure, $FrdTenure_{ij}$, as measured by the number of days passed from the formation of online friend relationship to the rating of the focal user. First, we regress the absolute difference between the focal users' ratings and their friends' average ratings ($RatingDiff_{ij} = |Rating_{ij} - AvgFrdRating_{ij}|$) on $FrdTenure_{ij}$, controlling for user fixed effects. As shown in column (1) of Table 5, we find no statistically significant effect of $FrdTenure_{ij}$. We then adopt a model similar to the one used in the main analysis and regress the focal users' ratings on their friends' average ratings with the interaction between $AvgFrdRating_{ij}$ and $FrdTenure_{ij}$ (Table 5, column 2). Again, we find no evidence that older friends are more similar than newer ones.

To lend further support, we consider the case in which at least two of the focal users' friends had given ratings to the book before the focal rating. We categorize these friends' ratings into an old friend rating ($OldFrdRating_{ij}$) and a new friend rating ($NewFrdRating_{ij}$) with respect to the median tenure of the friend ties. Hence for each focal rating in the sample, we have two friend ratings, $OldFrdRating_{ij}$ and $NewFrdRating_{ij}$. If similarity is stronger between older friends, we should expect the difference $|Rating_{ij} - OldFrdRating_{ij}|$ to be smaller than the difference $|Rating_{ij} - NewFrdRating_{ij}|$. Interestingly, a paired t-test suggests the contrary (t(10,341)=2.24, p-value=0.03). There is actually marginally higher similarity between the ratings of the focal users and their newer friends. This is consistent with our intuition that users gradually develop new friend relationships based on common interest with the help from the site's collaborative filtering algorithm. Both user search and the algorithm depend on expressed preference data about a user that are accumulated overtime. As a result, later friends tend to be better targeted compared to earlier friends. Meanwhile, newer friends may get more attention from the focal user and thus exert higher influence. To the extent that older friends tend to appear more in the AFTER period and that focal users are marginally more similar to their newer friends, the effect we identify in the main analysis should be a conservative estimation of social influence.

6.3 Dyad Level Analysis

Our main analysis is a linear-in-mean model based on examining the similarity between a focal user's rating and the average rating of his friends (Brock and Durlauf 2001). The model's advantage is that we can easily aggregate the total social influence over the focal user into one variable and incorporate other variables into the model and study the moderation effects. The disadvantage is that using the average rating of friends may introduce inefficiency into the model due to dyad-level heterogeneity. Since each pair of friends is different from others in various ways, the similarity and the intensity of social influence may differ across the social links of the same focal user. If one focal rating's $AvgFrdRating_{ij}$ is calculated from many friends' ratings, the effect we estimate in the linear-in-mean model should be the mean influence from all those friends. Although this aggregation does not compromise our identification strategy (as we have the observations of the social-network structure on the individual level), a dyad-level model based on ratings of friend pairs offers an alternative estimation of social influence.

Following the same research design, we compare the rating similarity of books between the same two users before and after they become friends. After two users become friends, their taste similarity should not change. If their ratings become similar after they are friends, then the cause should be the visibility of the other user's ratings. As a result, if there is evidence of increased similarity after the formation of friend relationships, we can interpret the effect as social influence. In our data set, we identify 539,356 rating pairs by 137,987 pairs of friends.

Note that the unit of analysis in this model is a friend pair. The "earlier friends are more similar" concern does not arise. In addition, the unobserved similarity (homophily) between friends can be eliminated as dyad-level fixed effects. Specifically, we estimate the following model

$$RatingDiff_{ij} = \beta After_{ij} + d_i + \varepsilon_{ij}, \tag{2}$$

where $RatingDiff_{ij}$ is the absolute difference between the ratings of the two users in dyad i for book j, $After_{ij}$ is the indicator that both ratings were given before ($After_{ij} = 0$) or after ($After_{ij} = 1$) the formation of the friend relationship. Dyad-level fixed effects, d_i, control for unobserved friend-pair level effects. The parameter β gives the estimate for social influence.

Table 6: Additional Analysis – Dyad-Level Models

	(1)	(2)	(3)
	DV: $RatingDiff_{ij}$		
$After_{ij}$	-0.018**	-0.018**	-0.060**
	(0.007)	(0.008)	(0.025)
$TimeDiff\_ij$		6.78e-06	0.0002
		(0.001)	(0.002)
Number of Dyads	137,987	137,987	21,240
Number of Obs.	539,356	539,356	40,113
With-in R^2	0.0003	0.0003	0.0010

NOTES:

a. This table reports the estimation results of dyad-level analysis. Column 1 estimates social influence effect as reflect by the difference in rating similarity (as measured by the absolute difference of ratings of the same book) before/after the pair of users become online friends ($After_{ij}$) controlling for the dyad-level fixed effects. Column 2 includes the time between the two ratings as a control variable. In column 3, we consider a sub-sample of paired ratings that were given within a ten-day window.

b. $After_{ij}$ is a dummy variable indicating that both ratings in the pair are given before (=0) or after (=1) the formation of the friend relationship.

c. $TimeDiff_{ij}$ is the number of days between the two ratings in a pair.

d. Standard Errors are reported in parentheses. Significance levels are displayed as *** p<0.01, ** p<0.05, *p<0.1.

Estimation results, reported in Table 6, confirm the existence of social influence. Column (1) suggests that the rating difference significantly reduces after the friend pairs are formed. In model 2, we further examine whether there exists a recency effect (i.e., whether recent ratings have a larger impact) and do not find such evidence. The number of days between ratings in a dyad, $TimeDiff_{ij}$, is added to the main model, and it turns out to be non-significant. In both columns (1) and (2), based on the mean absolute difference between friends' ratings (0.7696), the rating difference decreases by 2.3% after the two become friends. Similarly, the effect of social influence can be estimated as 8.3% from model 3 (mean absolute difference = 0.7266).

One possible alternative explanation of our finding above is that users may read the reviews before they actually read the books. If this is true, then the rating association we identify only captures the effect of pre-consumption influence. To rule out this possibility, we conduct a robustness check based on our dyad-level model. In column (3) of Table 6, we require the two ratings in a pair to be given within a ten-day window.[14] This shrinks the sample to 40,113 rating pairs from 21,240 user pairs. The magnitude of social influence is significantly larger in this subsample. This finding suggests that our result is not driven by pre-consumption social influence between users.

Table 7: Importance of Leveraging Friend relationship Formation

	(1)	(2)
	DV: $RatingDiff_{ij}$	
$AfterFunction_{ij}$	-0.0105	0.0419
	(0.0219)	(0.0335)
$AvgFrdRating_{ij}$		-0.0669**
		(0.0323)
Number of Dyads	25,641	25,641
Number of Obs.	50,206	50,206
With-In R^2	0.0003	0.0003

NOTES:

a. This table reports the estimation results of a dyad-level analysis taking into account the introduction of the friend network function as an additional dummy. Model in column 1 estimates the effect of introducing the function. We add the friend relationship formation dummy to the model in column 2.
b. $AfterFunction_{ij}$ is a dummy variable indicating that both ratings in the pair are given before (=0) or after (=1) the introduction of the friend function.
c. $AfterFriendship_{ij}$ is a dummy variable indicating that both ratings in the pair are given before (=0) or after (=1) the formation of the friend relationship.
d. Standard Errors are reported in parentheses. Significance levels are displayed as *** p<0.01, ** p<0.05, *p<0.1.

Our next robustness check builds on the dyad-level analysis as well. It establishes that merely introducing the friend function in the system cannot lead to social influence. Social influence has to take place through the formation of friend relationship between users. In Table 7, we examine dyad-level rating similarity with two different timing dummies. $AfterFunction_{ij}$ is a dummy variable that equals one for the period after the introduction of the friend relationship function at the end of January of 2008.[15]

[14] Presumably, a reader who is influenced by others before he reads the book cannot finish reading a book within 10 days. In unreported regressions, changing the length of this window does not affect our result.

[15] All other models are based on data after the introduction of the friend relationship function.

$AfterFriendship_{ij}$ is a dummy variable that equals one if the pair of users become friends (i.e., it is equivalent to the $After_{ij}$ in Table 6). $AfterFriendship_{ij}$ is significantly negative in column 2 of Table 7, indicating that friend-rating similarity improved (i.e., smaller difference) after the formation of the friend relationship between the two users. $AfterFunction_{ij}$ is not significant, suggesting that social influence takes place only after the formation of friend relationships.

6.4 Additional Analysis of Rating Similarity in the BEFORE and AFTER periods

In the main analysis, we only consider the cases where friends' ratings are either all from the AFTER period or all from the BEFORE period (Panels A and B in Figure 2). Panel C in Figure 2 depicts the one situation in which the event of FR comes after A&F, but before B&F. Equation (1) cannot be fitted when this happens because the variable $After_{ij}$ would be ambiguous. We examine this sample of data in this section with two tests and offer supporting evidence of the validity of our results.

Table 8: Definitions

		Summary Statistics	
Variable Name	Definition	Mean	Std. Dev.
$Rating_{ij}$	Focal user i's rating for book j	4.109	0.858
$FrdRatingAfter_{ij}$	Average friends' rating for book j before the focal rating; focal rating is given after formation of these friend relationship	4.129	0.772
$FrdRatingBefore_{ij}$	Average friends' rating for book j before the focal rating; focal rating is given before formation of these friend relationship	4.125	0.767

Table 8 gives the variable definitions for this section. Our first test compares friends' ratings in the BEFORE period with those in the AFTER period. If a focal user's friends in the BEFORE period are indeed similar to his friends in the AFTER period, we would expect to see that the two groups of friends' ratings are close. In Panel C of Figure 2, this entails comparing A's rating ($FrdRatingAfter_{ij}$) with B's rating ($FrdRatingBefore_{ij}$).

The second test examines whether a focal user's rating is more similar to another user before or after they become friends or to another user after they become friends. That is, we would like to compare the difference between F's rating and A's rating with the difference between F's rating and B's rating. In the example given in Panel C of Figure 2, if there is social influence, we would expect to see that the difference between F and A ($\left|Rating_{ij} - FrdRatingAfter_{ij}\right|$) is smaller than the difference between F and B ($\left|Rating_{ij} - FrdRatingBefore_{ij}\right|$).

In our data set, we have 24,907 focal ratings (for 4,191 books by 7,871 focal users) that have friends' ratings from both the BEFORE period and the AFTER period.

Table 9: Additional Analysis – Rating Similarity in BEFORE and AFTER periods

	Statistical Comparison		
	t-Test	Wilcoxon Signed Rank Test	Sign Test for Matched Pairs
$FrdRatingAfter_{ij}$ versus $FrdRatingBefore_{ij}$	t(24,906)=0.530 p-value=0.596	p-value=0.644	p-value=0.866
$\left|Rating_{ij} - FrdRatingAfter_{ij}\right|$ versus $\left|Rating_{ij} - FrdRatingBefore_{ij}\right|$	t(24,906)=-2.446 p-value=0.007	p-value=0.013	p-value=0.023
$\left|Rating_{ij} - FrdRatingAfter_{ij}\right|$ versus $\left|Rating_{ij} - FrdRatingBefore_{ij}\right|$ Considers only the cases where $Rating_{ij}$ is between $FrdRatingAfter_{ij}$ and $FrdRatingBefore_{ij}$	t(14,366)=-2.799 p-value=0.002	p-value=0.003	p-value=0.004

We use paired t-tests to compare the means in each sample and report the results in Table 9. In the first test, there is no statistically significant difference between $FrdRatingAfter_{ij}$ and $FrdRatingBefore_{ij}$ (t(24,906)=0.53, p-value = 0.60). This result suggests that there is no difference between the two groups of friends' ratings. In other words, the focal user's friends' ratings do not change significantly after they become friends with the focal user.

In the second test, we compare $\left|Rating_{ij} - FrdRatingAfter_{ij}\right|$ and $\left|Rating_{ij} - FrdRatingBefore_{ij}\right|$ The paired t-test confirms our prediction that the focal users' ratings are closer to their friends' ratings in the AFTER period (t(24,906)=-2.45, p-value<0.01). To alleviate possible concerns of non-linearity in the distribution of ratings, we also conduct the Wilcoxon Signed Rank test and the sign test, which are nonparametric methods to test equivalence between two random variables. Both tests reject equality at the 5% significance level. The same results are obtained with the third test when we further require that $Rating_{ij}$ lies between $FrdRatingBefore_{ij}$ and $FrdRatingAfter_{ij}$.

6.5 Do Public Ratings Have the Same Conformity Pressure?

In this section, we assess possible unobserved systematic changes in how users respond to previous ratings. Suppose users tend to agree more with each other's opinion over time, even without social influence from making friends, one would still observe ratings becoming more similar. To offer further support that the rating changes we identify are attributable to friend relationship formation, we examine the effect of the average ratings of all users.

In Table 10, in addition to using the average of prior friends' ratings as the independent variable, we consider the treatment effect on the average of all previous ratings, $AvgRating_{ij}$. As our result reported in column (1) of Table 10 suggests, controlling for the friends' ratings, we find no significant treatment effect on public ratings. That is, increase in rating similarity only takes place with friend ratings, even when we introduce public ratings into the model. This result supports that our identified social influence is indeed due to conformity among friends. Interestingly, when we only consider the treatment effect of public ratings (column (2) of Table 10), there seems to be a significant treatment effect on $AvgRating_{ij}$. The focal users' ratings in the AFTER cases are more similar to the average ratings from the public. It suggests that social influence among online friends results in increased similarity in the public ratings. In other words, with online social-networking functions, we see more unanimity than diversity in online ratings. This is in contrast with previous studies that show later raters tend to deviate from public ratings when social-networking feature are not considered (e.g. Moe and Schweidel 2012; Wu and Huberman 2008).

Table 10: Examining the Effect of Public Ratings

	(1)	(2)
	DV: $Rating_{ij}$	
$AvgFrdRating_{ij}$	2.64e-02***	5.09e-02***
	(4.04e-03)	(2.87e-03)
$AvgRating_{ij}$	-7.54e-01***	-7.86e-01***
	(6.98e-02)	(6.97e-02)
$After_{ij}$	-3.14e-03*	-3.26e-03*
	(1.80e-03)	(1.80e-03)
$AvgFrdRating_{ij} \times After_{ij}$	4.84e-02***	
	(5.61e-03)	
$AvgRating_{ij} \times After_{ij}$	7.92e-03	6.40e-02***
	(1.66e-02)	(1.53e-02)
Other Controls	Yes	Yes
User-Fixed Effects	Yes	Yes
Book-Fixed Effects	Yes	Yes
Number of Users	33,605	33,605
Number of Books	20,480	20,480
Number of Obs.	171,588	171,588
Adjusted R^2	0.337	0.336

NOTES:

a. In this table, we add the interaction between $After_{ij}$ and $AvgRating_{ij}$ to the main model to examine the systematic change in the tendency of a user to follow others' rating.
b. All controls in the main analysis are included. Book- and user-fixed effects are included in the estimation.
c. Standard Errors are reported in parentheses. Significance levels are displayed as *** p<0.01, ** p<0.05, *p<0.1.

6.6 Contingent Social Influence

The main objective of this paper is to empirically identify the existence of social influence from friends in the generation of online product ratings. Leveraging on the temporal sequence of ratings and formation of friend relationships, we propose a quasi-experiment research design that clearly identify social influence in online ratings. Based on this, it is of great importance to go forward to study conditions under which social influence is more salient (Godes 2011).

The exploration of potential contingent factors offers many utilities to the current study. First, we would like to demonstrate that our methodology is well suited for studying such moderators in similar contexts. When contingent factors are different or when additional covariates are available (e.g., user demographics, product characteristics, etc.) in similar situations, the empirical strategy can be easily adapted to examine a different set of moderators. Second, an examination of moderators of social influence in online product ratings is interesting and important in and of itself. Answering the "why, when, and how" questions of social influence holds promise as a means to deepening our understanding of the underlying mechanisms through which social influences take place and offers the potential of providing practical guidance for marketing managers and system designers to improve their use of social-networking features. Third, contingency revealed from the analysis suggests that the identified social influence changes opinion expression rather than induces shift in user taste.

First, estimation results reported in columns (1) and (2) of Table 11 investigate the moderating role of the valence of friend rating. In the online ratings context, extreme ratings convey strong feelings about a product and have more significant impacts on others. Based on the summary statistics reported in Table 1, which reveal that online ratings are generally positive, we categorize a rating as extremely positive if it is higher than 4 stars and extremely negative if it is lower than 3 stars. We then replicate our main model on two subsamples, a sample with extremely negative friends' ratings (column 1 of Table 11) and a sample with extremely positive friends' ratings (column 2 of Table 11). Estimation results suggest that social influence is more salient for extremely negative ratings, while there is no such evidence in the subsample with extremely positive ratings. This suggests that negative evaluations exert higher conformity pressure and friends' ratings do not have a significant impact on the focal users' ratings in a positive rating environment.

Second, in column (3) of Table 11, we further include contingency factors that capture the characteristics of the friends' ratings, books being rated, as well as focal users in our data set. The selection of these variables is guided by relevant discussions in the social influence literature and constrained by data availability. Table 12 summarizes the variables considered, gives the rationale for exploring these factors, and shows the empirical findings. The moderating effects are tested with three-way interaction terms. For example, for $Recency_{ij}$, the estimate reported in the Contingent Factor part in Table 11 corresponds to the regression coefficient for $Recency_{ij} \times AvgFrdRating_{ij} \times$

$After_{ij}$.

Table 11: Additional Analysis – Contingent Social Influence

	(1)	(2)	(3)
	DV: $Rating_{ij}$ ($AvgFrdRating_{ij} \leq 3$)	DV: $Rating_{ij}$ ($AvgFrdRating_{ij} > 4$)	DV: $Rating_{ij}$
$AvgFrdRating_{ij}$	1.48e-02	-2.01e-02	2.41e-02***
	(1.31e-02)	(3.13e-02)	(4.49e-03)
$After_{ij}$	2.71e-03	1.88e-03	-5.02e-03***
	(9.85e-03)	(9.20e-03)	(1.90e-03)
$AvgFrdRating_{ij}$	6.23e-02***	1.81e-02	5.98e-02***
$\times After_{ij}$	(1.89e-02)	(4.35e-02)	(5.87e-03)
Contingent Factors:			
$Recency_{ij}$			-1.13e-02***
			(3.54e-03)
$BookAge_{ij}$			2.67e-02***
			(7.85e-03)
$RatingIntensity_{ij}$			3.58e-03
			(4.96e-03)
$NumFrd_{ij}$			-1.94e-02***
			(5.41e-03)
$UserAge_{ij}$			3.08e-03
			(2.83e-03)
Control Variables	Yes	Yes	Yes
User-Fixed Effects	Yes	Yes	Yes
Book-Fixed Effects	Yes	Yes	Yes
Number of Users	30,578	65,609	33,605
Number of Books	21,596	49,519	20,480
Number of Obs.	33,038	70,930	171,588
Adjusted R^2	0.356	0.303	0.337

NOTES:

a. This table reports estimation results of moderating effects. In column 1, the main model is replicated on a subsample where the $AvgFrdRating_{ij} \leq 3$ (Extremely Negative). In column 2, we consider another subsample where the $AvgFrdRating_{ij} > 4$ (Extremely positive). In column 3, we include additional contingent factors to the model.

b. In column 3, moderating effects are tested with three-way interaction terms. For example, for $Recency_{ij}$, the estimate reported in the Contingent Factor part corresponds to the regression coefficient for $Recency_{ij} \times AvgFrdRating_{ij} \times After_{ij}$. All the second order interactions are included in the model (Irwin and McClelland 2001).

c. Standard Errors are reported in parentheses. Significance levels are displayed as *** p<0.01, ** p<0.05, *p<0.1.

First, we find that more recent friends' ratings indeed have a higher influence on focal ratings. This result suggests that friends' social influence in online WOM tapers off over time. As time passes, previous friends' ratings can become less relevant to focal users. Second, friends' influence is more salient for older books and books being intensively rated in the system. This suggests that users conform to their friends in an attempt to develop and manage the relationships that define themselves in the community. This finding also suggests that while users could learn from others' rating in the rating generation, especially when the post-adoption evaluation uncertainty is high, it might not be the dominant social influence mechanism through which social nudge in online ratings works. Third, having more friends implies a reduction in the average salience of friends' social influence to a user. As users expand their friend networks, they pay less attention to each of their friends.[16] This finding is consistent with the recent literature on online social networks which suggests that it is harder to attend to all friends when friend networks get bigger (Trusov et al. 2010; Watts and Dodds 2007). Finally, we do not find a significant moderating effect of user experience as measured by $UserAge_{ij}$. This suggests that experienced users are subject to similar social influence as new users.

Our attempt to theoretically explore contingencies in friends' social influence is summarized in Table 12. Overall, this exploratory analysis finds that friends' social influence is stronger for more popular books, and for users who have relatively fewer friends. In addition, extremely negative and more recent friends' ratings tend to have more salient influence.

[16] In our sample, less than 10% of the focal users' ratings have more than 3 prior friends' ratings.

Table 12: Moderating Role of Rating, Book and User Characteristics

	Rationale	Finding
$Recency_{ij}$ (Reverse Coded)	According to Latané (1981), the odds of being influenced by others increases with the immediacy to them in time and space. Meanwhile, the accessibility-diagnosticity theory suggests that more recent ratings are perceived as of higher relevance to the rating task at hand (Feldman and Lynch 1988) Consistent with this notion, the extent to which friends' ratings influence focal users' ratings can depend on how recently the friends posted their ratings.	Significant & Positive
$BookAge_{ij}$	Prior literature suggests that individuals want to be similar to their friends (in-group members) while at the same time staying different from "out-group" members to maintain clear identity (Berger and Heath 2007, 2008; Escalas and Bettman 2005). Books that has been reviewed long before the focal rating presents a rating environment where abundant out-group ratings present, which strengthen the incentive to conform to friends.	Significant & Positive
$RatingIntensity_{ij}$	Similar to the above discussion, books that are intensively reviewed present rating environments in which it is important to differentiate oneself by conforming to friends.	Non-significant & Positive
$NumFrd_{ij}$	When a user has a large social network, he is proportionally less likely to pay attention to one specific rating left by a friend. It has been demonstrated in lab experiments that as the number of a group increases, each person has less of an impact (Latané 1981). Further, it has been revealed that only a fraction of online friends actually have impacts (Trusov et al. 2010). Thus, it is expected social influence is less significant for users with larger friend networks.	Significant & Negative
$UserAge_{ij}$	The literature suggests that users' domain knowledge determines their susceptibility to influence from others in investment decisions (Hoffmann and Broekhuizen 2009), brand choices (Witt and Bruce 1972), and products (Locander and Hermann 1979; Mangleburg et al. 2004). Less experience users of the rating system face higher uncertainty in giving ratings and thus are more inclined to anchor his ratings on friends' ratings.	Non-significant & Positive

7 Conclusion

In this paper, we investigate friends' peer influence in post-adoption opinion reporting using book ratings and online social-network data from a popular online rating website in China. Our methodology exploits the temporal sequence of formation of online friend relationships and rating activities and offers a quasi-experimental methodology to identify the presence of friends' social influence in the generation of online ratings. We examine the validity of our research design with numerous tests to extend our understanding about friends' influence in online social networks. We find that social influence is stronger for more popular books and for users with relatively smaller friend networks. In addition, extremely negative and more recent friends' ratings tend to exert higher influence.

Our results offer important managerial implications to marketers and online rating-system designers. Systems designers, depending on their objectives, can use our results to nudge their users (e.g., create or avoid social influence in opinions by creating new functions or changing existing ones to alter the social context of the rating environment). For example, rating sites can develop algorithms to recommend reviews not subject to influence of social ties, highlight only reviews from users who do not have friends posted before them, or post a warning sign whenever it is suspected that a review might be influenced by friends, etc. For marketing practitioners, it is important to identify the early adopters and take their social influence into consideration when making plans to respond to online consumer ratings and reviews. We argue that WOM management in social networks can be very different from the situation when ratings are given independently. Our additional analysis of the moderating effects of book and user characteristics can help managers effectively target their efforts to achieve marketing goals. For example, managers are likely to expend more resources on products that receive intensive user reviews, but our analysis shows that peer influence is also greater in this case, which may potentially undermine these marketing efforts. The fact that peer influence is stronger for older books suggests that for products with long life cycles, peer influence in ratings should be carefully considered. Our finding that social influence is stronger for users with small social networks suggests that the issue of social influence in online ratings is particularly problematic in online ratings systems with newly introduced social networks.

Our paper makes several contributions to the literature.

First, our contribution lies in proposing a method to assess the level of friends' social influence in online product ratings, after eliminating the homophily effect that often confounds the identification of social effects. Our approach can be easily replicated in other online rating systems with social-networking features and does not require changes in the systems' functionality. The method makes it possible to evaluate peer influence in user-generated content production when only historical and observational data are available and when randomized experiments are hard to design or deploy. Compared to other methods proposed in the literature to identify friends' social influence, the quasi-experimental design also has a positive feature of being computationally less demanding and theoretically less constrained. Our empirical analysis demonstrates the power of this method in dealing with big dataset with millions of ratings and social-network ties.

Second, this study differs from previous studies of social influence in two important ways. (a) While previous studies examine social influence in adoption, we study post-adoption opinion reporting. The underlying mechanisms through which social influences take place can be markedly different. (b) While previous studies examine the public's social influence in the generation of online product ratings, we specifically show that friends exert disproportionately higher influence than the public.

Third, as shown by our exploration of moderators, our research design can be easily adapted to consider contingencies in social influences. The current exploration not only offer managerial implications for managers and system designers to develop better online rating systems, but also opens the door for future theoretical investigations of the underlying processes of friends' social influence on opinions.

Last but not least, we are among the first to document friends' influence in online ratings arising from social-networking functions that are common among UGC sites. Although social networks are generally valuable to enable efficient communication of information as well as motivating participation, social influence in opinion expression may render online ratings less useful in conveying new information. Compared to other behavioral tendencies in online ratings reported in the literature, the impact of friend influence is not easily corrected, precisely because of the evolving nature of social networks. When friends are updated about others' ratings and are influenced by them, online ratings may become path dependent. Managers should be aware of social network's potential impacts on the value of their rating systems.

We conclude the paper by offering some caveats and limitations of our method. Associated with these challenges, there are valuable opportunities for future research. First, when users cannot perfectly observe the product's true quality even after consumption, as in the case of credence goods, it is possible for them to interpret their friends' ratings as quality signals. Although books (studied in this paper) and other information goods are generally considered to be experience goods in the literature (Shapiro and Varian 1999), it is difficult to completely rule out the possibility that social influence may arise from learning if there is post-consumption uncertainty in evaluating a book's quality. Our analysis of the moderating effects suggests that this concern is not significant in our context of online book ratings. Studies of other products should not take this result as granted. Valuable contributions can be made by future research to identify the exact mechanism through which social influence takes place.

Second, when users' evaluations are significantly different from their friends, they may choose not to post anything (Dellarocas 2006). While this is also a type of social influence caused by social ties, its implication on the rating systems can be different from the social nudge we find in this paper. However, our data do not allow us to investigate the significance of this type of influence directly.

Finally, because of limitations in the data set, we cannot examine the impact on sales. Along this direction, Moe and Trusov (2011) and Lee et al. (2011) make valuable contributions. At the same time, due to data limitation, we were not able to present a full-fledged theoretical analysis about contingencies in social influence. Future research should extend our exploratory discussion about contingencies and fully establish a theoretical framework about online social influence.

References

Angrist, J. D., and Pischke, J.-S. 2010. The Credibility Revolution in Empirical Economics: How Better Research Design Is Taking the Con out of Econometrics. *Journal of Economic Perspectives* **24**(2) 3–30.

Antweiler, W., and Frank, M. Z. 2004. Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. *Journal of Finance* **59**(3) 1259–1294.

Aral, S., Muchnik, L., and Sundararajan, A. 2009. Distinguishing Influence-Based Contagion from Homophily-Driven Diffusion in Dynamic Networks. *Proceedings of the National Academy of Sciences* **106**(51) 21544–21549.

Aral, S., and Walker, D. 2011. Creating Social Contagion Through Viral Product Design: A Randomized Trial of Peer Influence in Networks. *Management Science* **57**(9) 1623–1639.

Aral, S., and Walker, D. 2012. Identifying Influential and Susceptible Members of Social Networks. *Science* **337** (6092) 337–341.

Banerjee, A. V. 1992. A Simple Model of Herd Behavior. *Quarterly Journal of Economics* **107**(3) 797–817.

Berger, J., and Heath, C. 2007. Where Consumers Diverge from Others: Identity Signaling and Product Domains. *Journal of Consumer Research* **34**(2) 121–134.

Berger, J., and Heath, C. 2008. Who Drives Divergence? Identity Signaling, Outgroup Dissimilarity, and The Abandonment of Cultural Tastes. *Journal of Personality and Social Psychology* **95**(3) 593–607.

Bikhchandani, S., Hirshleifer, D., and Welch, I. 1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy* **100**(5) 992–1026.

Bollen, K., and Pearl, J. 2013. Eight Myths About Causality and Structural Equation Models. *Handbook of Causal Analysis for Social Research*, S. L. Morgan (ed.), 301–328.

Bolton, G. E., Katok, E., and Ockenfels, A. 2004. How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation. *Management Science* **50**(11) 1587–1602.

Bramoullé, Y., Djebbari, H., and Fortin, B. 2009. Identification of Peer Effects Through Social Networks. *Journal of Econometrics* **150**(1) 41–55.

Brock, W. A., and Durlauf, S. N. 2001. Interactions-Based Models. *Handbook of Econometrics* **5** 3297–3380.

Brown, J. R., Ivković, Z., Smith, P. A., and Weisbenner, S. 2008. Neighbors Matter: Causal Community Effects and Stock Market Participation. *Journal of Finance* **63**(3) 1509–1531.

Van den Bulte, C., and Lilien, G. L. 2001. Medical Innovation Revisited: Social Contagion versus Marketing Effort. *The American Journal of Sociology* **106**(5) 1409–1435.

Burnkrant, R. E., and Cousineau, A. 1975. Informational and Normative Social Influence in Buyer Behavior. *The Journal of Consumer Research* **2**(3) 206–215.

Cai, H., Chen, Y., and Fang, H. 2009. Observational Learning: Evidence from a Randomized Natural Field Experiment. *American Economic Review* **99**(3) 864–882.

Campbell, D. T., and Stanley, J. C. 1963. *Experimental and Quasi-Experimental Designs for Research*, (1st ed, Vol. 84) Wadsworth Publishing.

Chen, Y., and Xie, J. 2005. Third-Party Product Review and Firm Marketing Strategy. *Marketing Science* **24**(2) 218–240.

Chevalier, J. A., and Mayzlin, D. 2006. The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research* **43**(3) 345–354.

Chintagunta, P. K., Gopinath, S., and Venkataraman, S. 2010. The Effects of Online User Reviews on Movie Box Office Performance: Accounting for Sequential Rollout and Aggregation Across Local Markets. *Marketing Science* **29**(5) 944–957.

Cialdini, C., and Trost, M. R. 1998. Social Influence: Social Norms, Conformity and Compliance. *Handbook of Social Psychology, Volume 2*, G. Lindzey, D. Gilbert, and S. T. Fiske (eds.), (Vol. 2) 151–192.

Cialdini, R. B., and Goldstein, N. J. 2004. Social influence: Compliance and conformity. *Annual Review of Psychology* **55**(1) 591–621.

Cohen, J. B., and Golden, E. 1972. Informational Social Influence and Product Evaluation. *Journal of Applied Psychology* **56**(1) 54–59.

Conley, T. G., and Udry, C. R. 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* **100**(1) 35–69.

Crandall, D., Cosley, D., Huttenlocher, D., Kleinberg, J., and Suri, S. 2008. Feedback Effects between Similarity and Social Influence in Online Communities. *Proc. 14th ACM SIGKDD Intl. Conf. on Knowledge Discovery and Data Mining*

Dellarocas, C. 2006. Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms. *Management Science* **52**(10) 1577.

Dellarocas, C., and Wood, C. A. 2008. The Sound of Silence in Online Feedback: Estimating Trading Risks in The Presence of Reporting Bias. *Management Science* **54**(3) 460–476.

Dellarocas, C., Zhang, X. (Michael), and Awad, N. F. 2007. Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing* **21**(4) 23–45.

Deutsch, M., and Gerard, H. B. 1955. A Study of Normative and Informational Social Influences upon Individual Judgment. *Journal of Abnormal and Social Psychology* **51**(3) 629–636.

Duan, W., Gu, B., and Whinston, A. B. 2008. The Dynamics of Online Word-of-Mouth and Product Sales–An Empirical Investigation of the Movie Industry. *Journal of Retailing* **84**(2) 233–242.

Duflo, E., and Saez, E. 2003. The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment. *Quarterly Journal of Economics* **118**(3) 815–842.

Dulleck, U., and Kerschbamer, R. 2006. On Doctors, Mechanics, and Computer Specialists: The Economics of Credence Goods. *Journal of Economic Literature* **44**(1) 5–42.

Escalas, J. E., and Bettman, J. R. 2005. Self-Construal, Reference Groups, and Brand Meaning. *Journal of Consumer Research* **32**(3) 378–389.

Feldman, J. M., and Lynch, J. G. J. 1988. Self-Generated Validity and Other Effects of Measurement on Belief, Attitude, Intention, and Behavior. *Journal of Applied Psychology* **73**(3) 421–435.

Foster, G. 2006. It’s Not Your Peers, and It's Not Your Friends: Some Progress Toward Understanding the Educational Peer Effect Mechanism. *Journal of Public Economics* **90**(8-9) 1455–1475.

Godes, D. 2011. Commentary--Invited Comment on “Opinion Leadership and Social Contagion in New Product Diffusion.” *Marketing Science* **30**(2) 224–229.

Godes, D., and Mayzlin, D. 2004. Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science* **23**(4) 545–560.

Godes, D., and Silva, J. C. 2011. Sequential and Temporal Dynamics of Online Opinion. *Marketing Science* **31**(3) 448–473.

Hoffmann, A., and Broekhuizen, T. 2009. Susceptibility to and Impact of Interpersonal Influence in an Investment Context. *Journal of the Academy of Marketing Science* **37**(4) 488–503.

Hu, N., Bose, I., Gao, Y., and Liu, L. 2011. Manipulation in Digital Word-of-Mouth: A Reality Check for Book Reviews. *Decision Support Systems* **50**(3) 627–635.

Hu, N., Pavlou, P. A., and Zhang, J. 2007. Why do Online Product Reviews have a J-shaped Distribution? Overcoming Biases in Online Word-of-Mouth Communication.

Irwin, J. R., and McClelland, G. H. 2001. Misleading Heuristics and Moderated Multiple Regression Models. *Journal of Marketing Research* **38**(1) 100–109.

Iyengar, R., Van den Bulte, C., and Valente, T. W. 2011. Opinion Leadership and Social Contagion in New Product Diffusion. *Marketing Science* **30**(2) 195–212.

Kutner, M., Nachtsheim, C., and Neter, J. 2004. *Applied Linear Regression Models*, (4th ed) McGraw-Hill/Irwin.

Latané, B. 1981. The Psychology of Social Impact. *American Psychologist* **36**(4) 343–356.

Lazarsfeld, P. F., and Merton, R. K. 1954. Friendship as a Social Process: A Substantive and Methodological Analysis. *Freedom and Control in Modern Society*, M. Berger, T. Abel, and C. Page (eds.), (Vol. 18) 18–66.

Lee, Y. J., Tan, Y., and Hosanagar, K. 2011. Do I Follow My Friends or the Crowds? Examining Informational Cascades in Online Movie Reviews.

Lewis, K. 2011. The Co-evolution of Social Network Ties and Online Privacy Behavior. *Privacy Online*, S. Trepte and L. Reinecke (eds.), 91–109.

Li, X., and Hitt, L. M. 2008. Self-Selection and Information Role of Online Product Reviews. *Information Systems Research* **19**(4) 456–474.

Liu, Y. 2006. Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing* **70**(3) 74–89.

Locander, W. B., and Hermann, P. W. 1979. The Effect of Self-Confidence and Anxiety on Information Seeking in Consumer Risk Reduction. *Journal of Marketing Research* **16**(2) 268–274.

Mangleburg, T. F., Doney, P. M., and Bristol, T. 2004. Shopping with friends and teens’ susceptibility to peer influence. *Journal of Retailing* **80**(2) 101–116.

Manski, C. F. 1993. Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* **60**(3) 531–542.

Marquardt, D. W. 1970. Generalized Inverses, Ridge Regression, Biased Linear Estimation, and Nonlinear Estimation. *Technometrics* **12**(3) 591–612.

Marsden, P. V., and Friedkin, N. E. 1993. Network Studies of Social Influence. *Sociological Methods & Research* **22**(1) 127–151.
Mas, A., and Moretti, E. 2009. Peers at Work. *American Economic Review* **99**(1) 112–145.
McPherson, M., Smith-Lovin, L., and Cook, J. M. 2001. Birds of a Feather: Homophily. *Annual Review of Sociology* **27** 415–444.
Moe, W. W., and Schweidel, D. A. 2012. Online Product Opinions: Incidence, Evaluation and Evolution. *Marketing Science* **31**(3) 372–386.
Moe, W. W., Schweidel, D. A., and Trusov, M. 2011. Cutting through Online Chatter: White Noise or Resonating Insights? *Sloan Management Review* **53**(1) 14–16.
Moe, W. W., and Trusov, M. 2011. The Value of Social Dynamics in Online Product Ratings Forums. *Journal of Marketing Research* **48**(3) 444–456.
Moretti, E. 2011. Social Learning and Peer Effects in Consumption: Evidence from Movie Sales. *Review of Economic Studies* **78**(1) 356–393.
Muchnik, L., Aral, S., and Taylor, S. J. 2013. Social Influence Bias: A Randomized Experiment. *Science* **341** (6146) 647–651.
Pavlou, P. A., and Gefen, D. 2004. Building Effective Online Marketplaces with Institution-Based Trust. *Information Systems Research* **15**(1) 37–59.
Resnick, P., and Zeckhauser, R. 2002. Trust among Strangers in Internet Transactions: Empirical Analysis of eBay’s Reputation System. *Advances in Applied Microeconomics A Research Annual*, (M. R. Baye, ed.) **11**(12) 127–157.
Sacerdote, B. 2001. Peer Effects with Random Assignment: Results for Dartmouth Roommates. *Quarterly Journal of Economics* **116**(2) 681–704.
Salganik, M. J., Dodds, P. S., and Watts, D. J. 2006. Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. *Science* **311** (5762) 854–856.
Schlosser, A. E. 2005. Posting versus Lurking: Communicating in a Multiple Audience Context. *Journal of Consumer Research* **32**(2) 260–265.
Shapiro, C., and Varian, H. R. 1999. *Information Rules: a Strategic Guide to the Network Economy*, Harvard Business Press.
Snijders, T. A. B., Steglich, C. E. G., and Schweinberger, M. 2006. Modeling the Coevolution of Networks and Behavior. *Longitudinal Models in the Behavioral and Related Sciences*, K. van Montfort, J. Oud, and A. Satorra (eds.), 41–72.
Soetevent, A. R. 2006. Empirics of the Identification of Social Interactions; An Evaluation of the Approaches and Their Results. *Journal of Economic Surveys* **20**(2) 193–228.
Steglich, C., Snijders, T. A. B., and Pearson, M. 2010. Dynamic Networks and Behavior: Separating Selection from Influence. *Sociological Methodology* **40**(1) 329–393.
Summers, L. H. 1991. The Scientific Illusion in Empirical Macroeconomics. *Scandinavian Journal of Economics* **93**(2) 129.
Susarla, A., Oh, J.-H., and Tan, Y. 2012. Social Networks and the Diffusion of User-Generated Content: Evidence from YouTube. *Information Systems Research* **23**(1) 23–41.
Thaler, R. H., and Sunstein, C. R. 2008. *Nudge: Improving Decisions about Health, Wealth, and Happiness*, 312. Yale University Press.
Trusov, M., Bodapati, A. V, and Bucklin, R. E. 2010. Determining Influential Users in Internet Social Networks. *Journal of Marketing Research* **47**(4) 643–658.

Tucker, C. 2008. Identifying Formal and Informal Influence in Technology Adoption with Network Externalities. *Management Science* **54**(12) 2024–2038.

Watts, D. J., and Dodds, P. S. 2007. Influentials, Networks, and Public Opinion Formation. *Journal of Consumer Research* **34**(4) 441–458.

Witt, R. E., and Bruce, G. D. 1972. Group Influence and Brand Choice Congruence. *Journal of Marketing Research* **9**(4) 440–443.

Wu, F., and Huberman, B. A. 2008. How Public Opinion Forms. *Internet and Network Economics, Lecture Notes in Computer Science* **5385** 334–341.

Yoganarasimhan, H. 2012. Impact of Social Network Structure on Content Propagation: A Study using YouTube Data. *Quantitative Marketing and Economics* **10**(1) 111–150.

Zhang, J. 2010. The Sound of Silence: Observational Learning in the U.S. Kidney Market. *Marketing Science* **29**(2) 315–335.

Zhang, X., and Zhu, F. 2011. Group Size and Incentives to Contribute: A Natural Experiment at Chinese Wikipedia. *American Economic Review* **101**(4) 1601–1615.

Zhu, F., and Zhang, X. M. 2010. Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing* **74**(2) 133–148.