Management Science

Publication details, including instructions for authors and subscription information:
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MANAGEMENT SCIENCE
Vol. 61, No. 9, September 2015, pp. 2241–2258
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2014.2082

Do I Follow My Friends or the Crowd? Information Cascades in Online Movie Ratings

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Online product ratings are widely available on the Internet and are known to influence prospective buyers. An emerging literature has started to look at how ratings are generated and, in particular, how they are influenced by prior ratings. We study the social influence of prior ratings and, in particular, investigate any differential impact of prior ratings by strangers ("crowd") versus friends. We find evidence of both herding and differentiation behavior in crowd ratings wherein users' ratings are influenced positively or negatively by prior ratings depending on movie popularity. In contrast, friends' ratings always induce herding. Further, the presence of social networking reduces the likelihood of herding on prior ratings by the crowd. Finally, we find that an increase in the number of friends who can potentially observe a user's rating ("audience size") has a positive impact on ratings. These findings raise questions about the reliability of ratings as unbiased indicators of quality and advocate the need for techniques to de-bias rating systems.

Keywords: online word of mouth; ratings; social influences; informational cascades; latent variables; multilevel models; online social media
History: Received October 14, 2011; accepted September 1, 2014, by Sandra Slaughter, information systems. Published online in *Articles in Advance* April 15, 2015.

1. Introduction

Online user-generated reviews are an important source of product information on the Internet. They help prospective buyers in gaining from the experience of other users who have tried the product. A number of services have emerged over the last few years that attempt to integrate with online social network services (SNS) so that users can access reviews submitted by their friends in addition to those submitted by the rest of the online community. For example, in March 2009, Netflix integrated its Web application with Facebook to let users link their accounts at the two sites and share movie user ratings with their friends (Tirrell 2009). Similarly, Tripadvisor, Yelp, and several other prominent review websites have added features to allow users to identify reviews by friends.

Existing work on consumer reviews has analyzed the design and performance of eBay and Amazon-like online rating systems (see a survey in Dellarocas 2003). Most studies focus on the ex post valence and dispersion of online reviews and their relationship with sales. There are mixed findings in the literature on how online user reviews of a product influence its subsequent sales (Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Duan et al. 2009). Several studies report a positive impact of user reviews on book sales for online retailers such as Amazon.com or Barnesand-Noble.com (Chevalier and Mayzlin 2006, Li and Hitt 2008). Chen et al. (2004), however, report no effect of user ratings on sales from a similar data source of Amazon.com. Similarly, Duan et al. (2009) look at the impact of user ratings on software adoption and find that user ratings have no significant impact on the adoption of popular software. Liu (2006) and Duan et al. (2008) do not find any significant impact of rating valence on box office sales of movies but significant positive impact of the volume of reviews. In contrast, Chintagunta et al. (2010) account for pre-release advertising to show that it is the valence of online user reviews that seems to be the main driver of box office performance, and not the volume. Forman et al. (2008) find a strong association between user reviews and sales in the presence of reviewer identity disclosure.

Recent literature has examined the influence of prior ratings on subsequent users' ratings. In particular, researchers have found that there is a systematic trend in ratings. In a lab setting, Schlosser (2005) found that consumers adjust their reviews downward after observing prior negative reviews. She attributes this behavior to "self-presentational concerns" (p. 260), namely, that negative evaluators are more likely to be perceived as intelligent and competent and they are also likely to influence subsequent raters who also want to present themselves as intelligent. She also documents a "multiple audience effect" (p. 260), which indicates that consumers try to give more balanced opinions if they observe heterogeneous ratings in the community. Li and Hitt (2008) found a negative trend in product ratings and attribute it to dissimilar preferences between customers who buy early versus those who buy later. Wu and Huberman (2008) argue that people tend to follow a trend that has been created by previous opinions and then the trend becomes increasingly more extreme. They also found that a selection bias in the posting of reviews (e.g., reviewers have to pay to post their reviews) can reduce the extreme trend. Godes and Silva (2012) also found that the more ratings amassed for a product, the lower the ratings will be because of the increase in reviewers' dissimilarity. Moe and Trusov (2011) find that the posting of positive ratings encourages negative subsequent ratings (differentiation effect among later reviewers) and that disagreement among prior raters tends to discourage posting of extreme opinions by subsequent raters, which is consistent with the multiple audience effect. Moe and Schweidel (2012) found that less frequent reviewers imitate prior reviewers ("bandwagon behavior") whereas core active reviewers lead negative opinions in an effort to differentiate themselves.

All of these papers consider ratings from the entire online community without differentiating between ratings from friends and those from the rest of the community. However, ratings from friends may exert a different kind of influence relative to ratings by strangers ("crowd"). For instance, if a user can identify her friend as someone who is often critical in her assessment, this friend's low rating may become less salient. On the other hand, if this same friend provides a high rating, then that rating may be much more salient than a generous rating by the crowd. Further, reviewers' efforts to follow prior reviewers or differentiate themselves may differ based on whether the product is a popular product consumed by everyone versus a niche item consumed by few. There is evidence that found that reviewers are more likely to contribute a review for very obscure movies but also for very high-grossing movies (Dellarocas et al. 2010). Berger and Heath (2008) found that people's desire to differentiate themselves from others depends on product popularity. Another recent study also found that subsequent reviews tend to disagree more strongly with preceding reviews for less popular books (Hu and Li 2011).

Finally, many of these papers explore how later ratings differ from earlier ratings rather than how heterogeneous reviewers are influenced by different types of earlier ratings (and how this effect varies by product popularity). Muchnik et al. (2013) found that prior ratings bias individual rating behavior and that the level of bias depends on the topic and the source of prior ratings (friends versus enemies). Our study is complementary in nature but differs in its assessment of the role of product popularity and in its focus on separating the effect of social influence from that of surrounding product quality information that coexist when users review products. In this paper, we help fill this gap in the literature by investigating the factors that affect user ratings including social influence from prior ratings of others and friends and surrounding product information. In particular, we perform individual user-level analysis to address the following research questions:

- Do prior ratings of the crowd and those of friends differently influence a subsequent user's rating for a movie in an online community?
- Does the influence of different types of prior ratings differ based on the popularity of the movie?
- How does the social influence relate to the level of social interaction among users?

One of our main interests is in understanding how prior ratings by the crowd and friends may differently affect a subsequent user's rating. Our approach to examining the process of online user rating generation is grounded in informational cascades theory, which describes situations in which people observe others' actions and make the same choice independent of their own private signals (Banerjee 1992, Bikhchandani et al. 1992, Banerjee 1993, Bikhchandani et al. 1998). Although all moviegoers can observe publicly available movie related information (e.g., genre, MPAA rating, box office rank and sales, critics' reviews, advertising, etc.), each user has private quality information before or after watching the movie (Zhang 2010). At the time a user submits her rating, she has her post-purchase evaluation (Moe and Schweidel 2012) and can additionally observe prior ratings by other users. Although each prior user's rating is observable, reading all the individual reviews is often infeasible and, hence, people may only view aggregate information such as the average rating for the movie (Li and Hitt 2008). At typical social networking sites for movies, observing the average rating of the crowd or friends' ratings is quite effortless. However, these two different types of ratings provide significantly different quality information about a movie because friends' ratings are from people who are socially closer and the user has better context to understand friends' reviews. As such, ratings from friends can carry additional private information, but this is unlikely for a rating from the crowd. In the observational learning literature, it is shown theoretically that it can be rational for an individual to follow the behavior of preceding individuals without regard to her own private information (such as own postpurchase evaluation of a movie). This results in informational cascades (Bikhchandani et al. 1992). Herding describes a phenomenon in which individuals converge to a uniform social behavior (Banerjee 1992, Bikhchandani et al. 1998) through such cascades. Several empirically oriented studies (e.g., Anderson and Holt 1997, Celen and Kariv 2004) demonstrate the convergence in individuals' actions for dichotomous decision making in experimental environments. In contrast, a need to differentiate from others' ratings may exert a negative bias (Schlosser 2005) and such differentiation behavior has commonly been assumed in online user product review literature (Li and Hitt 2008, Moe and Trusov 2011). Hence, it is not clear when prior ratings may exert a positive or negative influence on future ratings and how this impact varies based on whether prior ratings are from the crowd or from one's own social circle. Finally, the anticipation that many other users in the community will later read one's rating can create social pressure and cause users to rate differently. We investigate these issues in this paper.

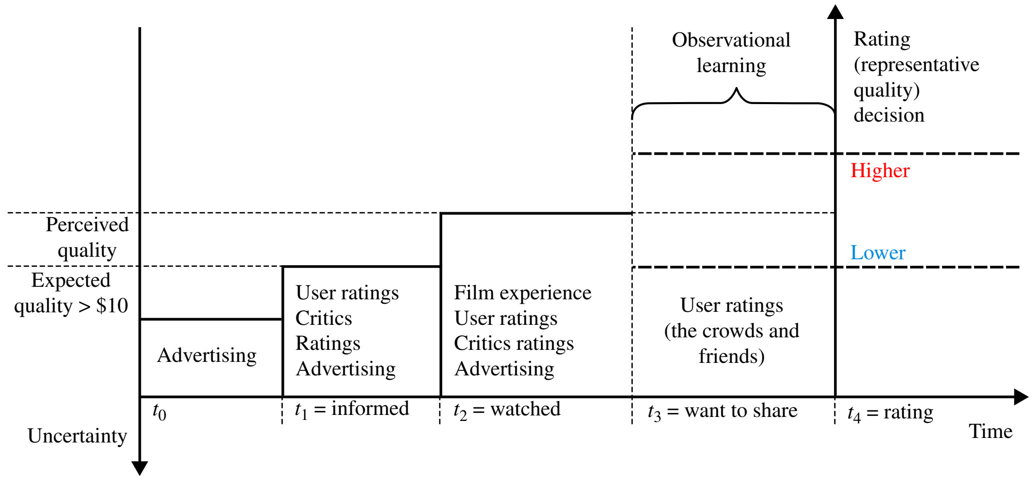
The challenge with the research arises from the fact that social influence often coexists with other sources of quality information, such as word-of-mouth (WOM) communication, network externalities, and firms' marketing mix variables. Hence, identifying the effects of social influence is difficult without controlling for the aforementioned components (Duan et al. 2009). Furthermore, individuals in the same reference group (e.g., users who watch and rate documentaries) may behave similarly in a common environment. Hence, it is difficult to distinguish real social effects from correlations due to homophily, known as the reflection problem (Manski 1993, Bramoullé et al. 2009). Thus, any analysis of the influence of past ratings on future ratings has to account for these effects. Although it is not feasible to rule out all possible confounds in a study based on field data, we need to isolate social influence from consumer heterogeneity, homophily (McPherson et al. 2001), and other relevant factors such as product characteristics and firms' marketing mix variables.

To address these issues, we gathered data from multiple sources to create a novel data set with rich information about user demographics, their social network information, and movie characteristics. Our primary data source is one of the top social movie sites (hereafter the social movie site). It had over 20 million unique users and about two billion user-generated movie reviews in 2008. Like other popular SNS (e.g., Facebook and MySpace), each user can create her own profile webpage on the social movie site and manage her online friends. It is an ideal setting for this study because of the following reasons. First, user ratings are time stamped, and the sequence of user ratings is easily identified. Second, ratings by friends are clearly separated from those by the crowd on the social movie site. Third, user-specific activities such as the history of reviews and number of friends in the service are identified. Fourth, similar to Zhang's (2010) evidence of observational learning in patients' sequential decisions of kidney transplant, online users in the community are unlikely to be influenced by other primary mechanisms behind uniform social behavior, such as sanctions of deviants, preferences for social identification (Kuksov 2007), and network effects (Sun et al. 2004) since providing online reviews is voluntary.

Our analysis of this data set indicates that there exists substantial social influence of prior ratings on subsequent users' ratings in an online social network community. We show the existence of both herding and differentiation effects in how subsequent users react to prior ratings by the crowd. Specifically, our results show that the differentiation effect leading subsequent reviewers to provide more negative ratings in response to more positive prior ratings by the crowd, becomes weaker as the popularity of a movie increases. For extremely popular movies, a herding effect can lead subsequent reviewers to provide more positive ratings in response to a positive trend of prior ratings. Interestingly, the herding effect of prior ratings by the crowd in popular movies can reduce with the increasing number of friends' prior ratings (social interaction about the movies increases). In contrast to crowd ratings, we find that only a herding effect is associated with friends' prior ratings, regardless of the popularity of a movie. The herding effect of friends' prior ratings becomes stronger as there are more prior ratings from friends (the popularity of a movie within her social network increases).

Finally, besides social influence from past ratings, another kind of social influence relates to the impact of anticipated future evaluation of one's own ratings by friends in one's social network. Our results also show that a user with a larger potential audience, measured by the number of friends in an online community, tends to provide more positive ratings. A user who anticipates that her reviews will be read by more friends may experience more pressure of providing a rationale for her negative ratings and may therefore be more inclined to provide positive ratings (Ahluwalia 2002).

Figure 1 (Color online) The Time Line of a User *j* to Rate a Movie *i*



2. Hypotheses Development

2.1. Herding vs. Differentiation in Crowd Ratings

Users make quality inferences based on multiple sources of information that are available at different times. These include information from advertisements, box office performance, user reviews, and eventually their own experience watching a movie (see Figure 1). The user then decides to rate the movie. The rating may primarily be influenced by the user's experience watching the movie. However, others' ratings can be influential references for the user. Like in dichotomous decision-making problems, users may combine the two sources of information (e.g., self-perceived quality and prior user ratings) to choose their rating for a movie. Reviewers may adjust their product evaluations depending on the opinions expressed by others (Schlosser 2005). These social influences may lead subsequent user ratings to become more positive or negative. For example, a tendency to conform with the majority may induce a user to choose a high rating rather than a low rating if the observed ratings of the crowd are high, i.e., exhibiting bandwagon behavior (Marsh 1985, McAllister and Studlar 1991, Moe and Schweidel 2012). Such tendency to conform to the action of others has been well documented in the information cascades and social proof literatures (e.g., Cialdini 2009). For example, Craig and Prkachin (1978) documented that participants administered shock felt lower levels of shock on pain indices if they observed other participants who were experiencing little or no pain. Some reasons for conformity even in the presence of contradicting private signals include rational expectations of making fewer errors when following the crowd, lower mental effort associated with following the crowd, and fear of loss of reputation from dissenting from the majority. Alternatively, there may be a negative trend in the online user ratings, due to the aforementioned self-presentational concerns, multiple audience, and dissimilarity effects (Schlosser 2005, Li and Hitt 2008, Moe and Trusov 2011). Therefore, it is not clear from the literature which effect, herding or differentiation, will dominate and under what circumstances one effect might become more salient. According to the theory of informational cascade, a user is more likely to realize that her reputation could be damaged if she dissents from the majority opinion of earlier responders (Kuran and Sunstein 1999). This fear of dissenting from majority opinions may become more salient when more people express their opinion. In contrast, when fewer opinions are expressed, the need to adhere to the majority opinion may be less salient. This suggests that a bandwagon effect may be more prominent when movies have lots of ratings. Furthermore, people are more likely to seek to differentiate themselves with niche products that contribute to self-expression than mainstream products that are universally adopted and unlikely to impact a person's ability to express their identity (Berger and Heath 2008). Thus, the need to differentiate oneself and better express one's identity may be more prominent for niche or less-popular items. Hence, we hypothesize that herding or bandwagon behavior should be more prominent for movies with lots of ratings, and differentiation behavior should be more prominent for movies that have fewer ratings:

Hypothesis 1 (H1). *There is a herding behavior of subsequent posters for movies with a large volume of user ratings and a differentiation behavior of subsequent posters for movies with a smaller volume of ratings.*

2.2. The Role of Social Interaction in User Ratings

Two types of ratings, those from the crowd and friends, may trigger observational learning in movie ratings. Our study seeks to identify the difference, if any, between the two types of observational learning—learning from the collective information about other users' ratings (*CROWDRA*) and that from information about friends' ratings (*FRWOM*). Unlike ratings from the crowd, ratings from friends can carry private information by means of communication tools (online chats and messaging) in SNS. Users can also better interpret ratings of friends based on their knowledge of these friends. Hence, friend ratings contain different information and may differently impact a user's choice of rating than ratings from the crowd.

Differentiation and herding effects are relevant for friends' ratings as well. In theory, differentiation in rating between friends should be low since closeness emerged as a result of similarity. Friends share many experiences that might lead them to develop similar attitudes, values, and behavior (Jussim and Osgood 1989). Berger and Heath (2008) show that individuals are more likely to diverge from outgroups (i.e., with people outside their social groups) than ingroups. Hence, regardless of the amount of reviews of the crowd for a movie, a user may choose a rating value similarly with her friends. We therefore propose the following:

Hypothesis 2 (H2). *The average of friends' ratings has a herding effect on subsequent ratings.*

Consider a movie reviewer who has no friend who has previously rated the movie. This reviewer is only influenced by crowd ratings. When a large number of reviews are available, cascades are likely because the user has no access to private signals of others (Banerjee 1992, Bikhchandani et al. 1992, Banerjee 1993, Bikhchandani et al. 1998) and therefore limited information to interpret their prior reviews. Suppose friends' ratings now become available to this reviewer. This reviewer now has access to private information of some of the previous reviewers and can better interpret the ratings. This should serve to reduce herding in crowd ratings. Further, crowd ratings may even become less salient when a user can observe ratings by friends. For example, Brown and Reingen (1987) show that when information from strong ties is available, weak ties are less likely to be activated. So, the greater the number of friends' ratings available to a user, the less likely that the user will be influenced by crowd ratings. Hence we hypothesize the following:

Hypothesis 3 (H3). *A subsequent user's herding behavior by CROWDRA, if it exists, decreases with an increase in the volume of her friends' ratings* (*Vol-FRWOM*) *for the movie that she rates.*

2.3. The Role of Social Pressure in User Ratings

Another kind of social pressure relates to that associated with the anticipation that one's own ratings will later be read and evaluated by others. In a controlled experimental setting, Ahluwalia (2002) finds that a negative bias will not emerge among those anticipating social interactions, and even reversal of a negative effect can be present. Specifically, she found that those with this kind of social pressure tended to enhance perceived diagnosticity of positive information and eliminate attitude-inconsistent negative information. The underlying social interaction in their study is between subjects who provide product evaluations and the company that produces the product. In SNS for movies, rating users' primary target audience is their friendship network and other members of the online community. However, even within a social network, a user may experience more pressure of providing a rationale of her negative rating with text reviews or online discussion. For example, in an experimental study in which participants were asked to have a short conversation about anything they wanted with other participants, Barasch and Berger (2014) found that communicating with a large group triggers self-presentational concerns and reduces the likelihood of people sharing negative content or experiences. As such, a user with more friends who can potentially observe a rating may be more affected by this kind of social pressure and, consequently, be more positive in her evaluations. We therefore propose the following:

Hypothesis 4 (H4). *A user with a large number of friends in an online community provides a more favorable rating than users with a smaller number of friends in the online community.*

3. Data Collection

We used software agents to collect data from several public websites for all movies released in theaters in the United States in 2007. Our data set contains information on movie characteristics and box office performance, and individual-level online user reviews. In addition, the data set includes weekly advertising spending for each movie. We also collected user-level review data from the social movie site for all the movies (see Table 1). All observable information about each user who has generated at least one movie rating is downloaded from the user profile page on the social movie site. The social movie site also provides information on friendship among users. Hence, this enables us not only to collect individual-level information such as gender, age, the number of ratings and reviews, and profile status (the number of times the profile has been viewed by other users and membership duration) on the website but also to partially observe friendship networks among users.

Table 1 Online Users and Movies Released in 2007

Data level	Dimension
Movie level	
—149 movies in 2007[a]	Movie characteristics
—54,274 user ratings during 16 weeks of the movies' release	Weekly advertising
	Weekly box office performance
	Ratings and reviews
Online movie reviewer level	
—28,160 individuals on the social movie site	Demographic and online profile
	Friendship
	Rating and text review

[a]There were a total of 371 movies in our original data. We excluded 84 movies that showed only partial data.

We first considered the intersection of our movie-level and user-level review data sets. Most ratings were generated within the first 16 weeks after the movies were released, as shown in Figure 2. Then, for our main analysis, we analyzed movies that have user ratings for at least 16 weeks after their release, and we only consider ratings in the 16-week window immediately after release to explore user rating behavior. An inspection of movie titles reveals that the 149 movies in the data set consist of popular, not-so popular, and niche ones in 2007. Table 2 provides a summary of user ratings for all movies in the original data and 149 movies for the 16-week-window data set in our analysis. Hence, our final data set for individual user-level analysis contains 28,160 individual users who reviewed and rated at least one of the 149 movies. These users generated 54,274 ratings in the first 16 weeks of the movies' release.

3.1. Dependent Variable

The key dependent variable in our individual level analysis is an online user's movie rating. Besides text reviews, users also submit a numeric rating for the movies from one of several predefined values. Although the cumulative average user rating trends of our sample movies are similar to the trends reported by Li and Hitt (2008) for online book ratings at Amazon.com (e.g., visually discernible patterns of declining and rising across times), weekly average user rating (noncumulative) of each movie in our sample presents an up-and-down pattern across weeks, as shown in Figure 2. The average rating for movies in our original data set is 7.45 out of 10, which is similar to the population means reported by

Figure 2 Online User Rating Trends After Movies Are Released for Four Sample Movies in Our Data Set

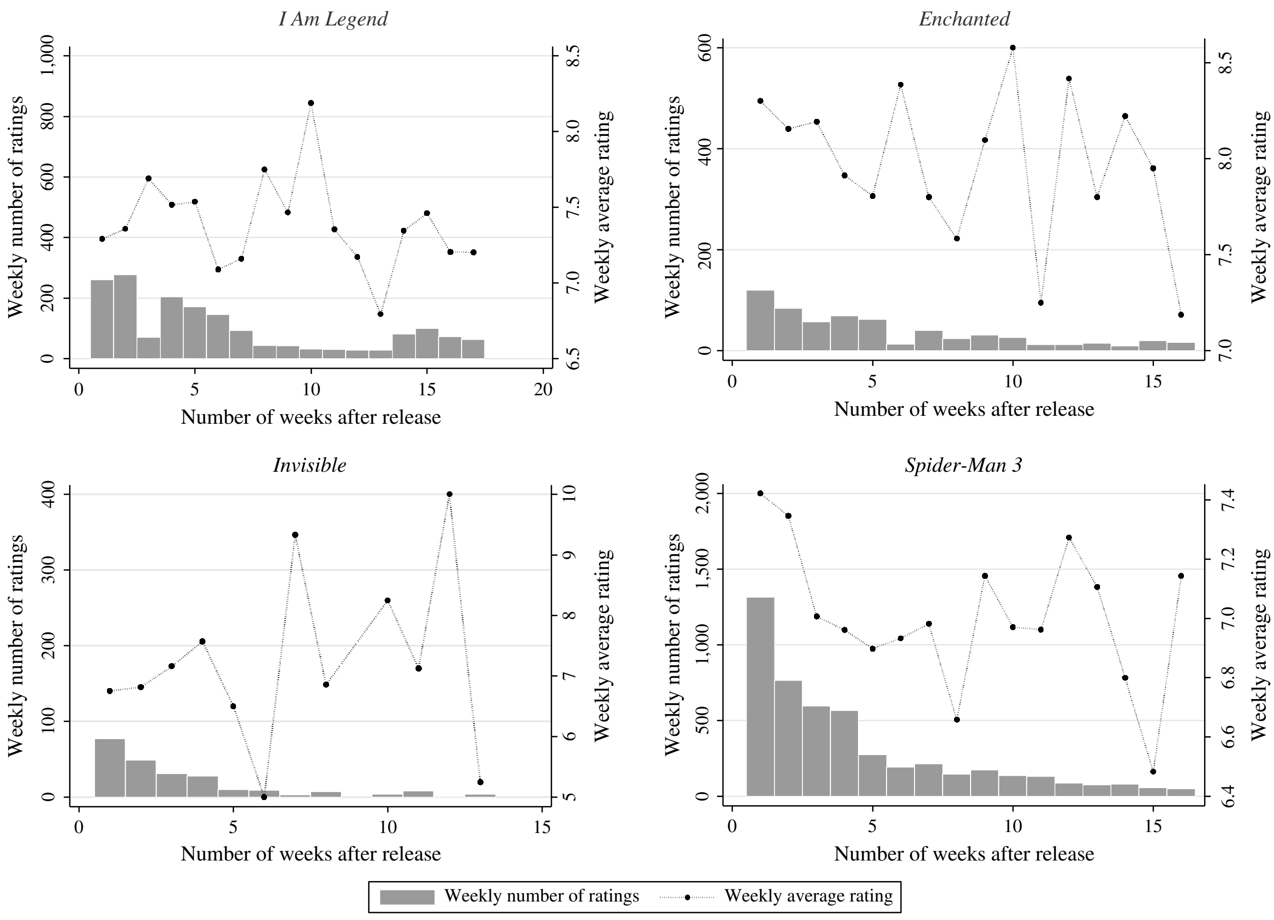


Table 2 Summary Statistics for the Number of Ratings and Average Ratings from the Original Data

	All 371 movies		149 movies in our analysis	
	Number of ratings per movie	Average ratings per movie	Number of ratings per movie	Average ratings per movie
Mean	2,289.55	7.45	1,628.59	7.72
Standard deviation	2,325.22	0.79	1,508.37	0.72
Percentile (%)				
1	35	4.69	42	5.23
5	161	6.18	95	6.52
10	288	6.57	157	6.87
25	699	6.89	440	7.12
50	1,369	7.40	880	7.92
75	2,656	8.12	3,094	8.33
90	6,349	8.40	3,954	8.58
95	6,696	8.53	4,564	8.58
99	7,666	8.57	4,564	8.72

Chevalier and Mayzlin (2006) and the sample means reported by Li and Hitt (2008).

3.2. Independent Variables: Quality Measures and User Characteristics

Our independent variables of most interest include observable quality measures and individual user characteristics. The valence and volume of ratings by preceding users and friends are the variables used to identify observational learning. *CROWDRA* is the average rating of all others (including online friends) who have rated the same movie before the focal user submits his rating. *Vol-CROWDRA* indicates volume of the prior ratings and gauges the popularity of a movie. Having an interaction between *CROWDRA* and *Vol-CROWDRA*, we can analyze how movie popularity affects the impact of *CROWDRA* on subsequent ratings. Similarly, *FRWOM* is the average rating by a user's online friends on the social movie site computed just prior to that user's rating. *Vol-FRWOM* indicates the number of those friend ratings for the same movie. Since only 20% of rating observations have *FRWOM*, *Vol-FRWOM* is used as an indicator for the presence (and volume) of friend rating. Hence, the interaction term, *CROWDRA* × *Vol-FRWOM*, explains how the impact of *CROWDRA* on a user rating changes given friends' rating(s). Since all user ratings we collected from the social movie site are time stamped, we could check whether a user's review is written before a friend's review is written. However, we could not identify when friendships are formed in our data. This is one of the limitations of the study. To ensure that this data limitation is not creating systematic biases in our findings, we provide results from a robustness check in a later section.

Additional product and quality information such as marketing effort and box office sales are also included as controls. Marketing effort is captured through the cumulative advertising spend (Cm.*Ad-Spending*). Users are continuously exposed to some degree of quality information through advertising, and we therefore use cumulative advertising spend instead of weekly spend.[1] Gross box office sales for a movie (*Cm.BoxOfficeSales*) in a given week are used to capture movie performance. The variance information factor (VIF) is less than three in our models, and therefore multicollinearity does not appear to be an issue.

Our independent variable set also includes important user-level variables that reflect a user's partial demographic characteristics, online activity, visibility, and social networks on the social movie site. These variables include *Gender* and *Age*, membership duration (*DaysofMembership*), the number of generated ratings (*Num.ofRatings*) and text reviews (*Num.ofReviews*), the number of times the user's profile has been viewed by others (*ProfileViews*), and the number of friends (*Num.ofFriends*) on the social movie site. Table 3 summarizes the independent variables.

4. Social Influence in Online User Movie Ratings

The multilevel structure of our data set creates several benefits to our study. First, at individual user level, a user's observed characteristics can appropriately control for individual user heterogeneity. Similarly, we can also control for movie level heterogeneity with observed movie characteristics. Also, a rating's time stamp of movie running week enables us to control for any unexplainable change across time. The data set records the ratings of the user on a 1–10 scale. Ideally, our dependent variable would be a continuous value of a user's satisfaction or postpurchase evaluation for a movie (Moe and Schweidel 2012). However, such an observation is unavailable. Therefore, we consider observed user ratings in a latent variable approach. Latent variables can represent the continuous values behind observed "coarsened" responses of user ratings, which are ordinal responses (Skrondal and Rabe-Hesketh 2004). Our modeling approach has three features to address some of the potential challenges with nonrandomized field data. First, our initial model specifies a user's latent movie evaluation as a function of heterogeneous baseline positivity (negativity), user characteristics, and social influence from other reviewers. Secondly, the latent response model is linked with the rating incidence model specifying a user's decision to submit a movie review in the online community. This enables us to account for a potential bias stemming from

[1] Estimation results were similar when we used weekly advertising spending.

Table 3 Data Descriptive Statistics

Dimension	Variable	Description	Mean	Min	Max
User level	*R*	Rating for the movie *i*	7.72	1	10
(28,160 users)	*Gender*[a]	Dummy for gender (female = 0)	0.48	0	1
	Age[a]	Age	25.35	13	107
	DaysofMembership	Membership days on the social movie site	686.76	118	1,286
	ProfileViews	Number of profiles viewed by others	609.5	1	258,794
	Num.ofFriends	Number of friends on the social movie site	50.89	1	830
	Num.ofRatings	Number of ratings on the social movie site	1,291.47	1	68,920
	Num.ofReviews	Number of text reviews on the social movie site	204.72	1	68,920
Movie level	CROWDRA	Average prior rating by other users for movie *i*	7.89	4	10
(149 movies)	*Vol-CROWDRA*	Number of prior ratings of other users for movie *i*	1,301.63	0	6,483
	FRWOM (10,877 obs.)[b]	Average prior rating by friends for movie *i*	7.91	1	10
	Vol-FRWOM	Number of prior friend ratings for movie *i*	0.55	0	114
	Cm.Ad-Spending	Cumulative advertising spending for movie *i* until week *t* in $ million	11.00	0.005	31.09
	Cm.BoxOfficeSales	Total gross of box office sales at week *t* in $ million	123.2	0.003	337
	RD	MPAA rating dummy (rated-R)	0.26	0	1
	PGD	MPAA rating dummy (rated-PG)	0.14	0	1
	PG-13D	MPAA rating dummy (rated-PG-13)	0.57	0	1
	Weeks	Movie playing week in theaters for movie *i* since it was released	4.65	1	16

[a]Since there are 8% of missing gender values and 35% of missing age values in our originally considered individuals (37,201), we exclude the individuals of missing gender and age. However, estimation results were similar when we imputed missing age values by organizing the cases by patterns of missing data so that the missing-value regressions can be conducted on other individual level variables.

[b]*FRWOM* is reported only for the observations that have at least one friend rating (10,877 observations out of 54,274).

self-selection of moviegoers who post their reviews on the social movie site. Thirdly, using a differential equation approach, the model attempts to address a reflection problem, wherein the correlation between social influence (ratings of the crowd) and similarity in a reference group (fans of a movie or genre tend to have similar preferences) can make the social effects endogenous at the individual level (Manski 1993). Although this does not guarantee that all possible confounds are accounted for, our approach allows us to address some of the more critical issues tied to nonrandomized field data.

4.1. Rating Response Model with Poster Heterogeneity

Following Moe and Schweidel (2012), first we assume that the rating contributed by a poster i is driven in large part by his or her post-movie j evaluation V_{ij}:

$$V_{ij} = \beta_{i0} + \beta_{1:n_1} X_i + \gamma_{j0}, \quad \text{where } \beta_{i0} \sim \mathrm{N}(\alpha, \sigma^2_{\beta_0}). \qquad (1)$$

The parameter β_{i0} is a poster i's level of baseline positivity (or negativity) and γ_{j0} allows for variation across movies. We further assume that β_{i0} can vary across posters and has a normal distribution with a mean of α and a standard deviation of σ_{β_0}. The variable X_i is an $n_1 \times 1$ vector of individual specific covariates that describe the poster's characteristics. The poster may adjust her post-movie evaluation because of the aforementioned social influence and the nature of the ratings environment. As such, we model the latent response R^*_{ijt} as a post-movie evaluation (perceived movie quality) for the movie j by the poster i at time t:

$$R^*_{ijt} = V_{ij} + \gamma_{1:n_2} Z_{jt(i)} + \varepsilon_{ijt}, \qquad (2)$$

where $Z_{j,\,t(i)}$ is an $n_2 \times 1$ vector of ratings environment covariates including a set of precedent posters' ratings information, e.g., *CROWDRA*, *FRWOM*, *Vol-CROWDRA*, and *Vol-FRWOM*, and a set of movie specific variables. The term ε_{ijt} is the idiosyncratic error with a mean of 0 and assumed to follow a standard normal distribution. The $1 \times n_1$ vector $\beta_{1:n_1}$ captures the effects of individual characteristics on a poster's post movie evaluation and the $1 \times n_2$ vector of $\gamma_{1:n_2}$ captures the impact that the social influence may have on an individual's posted rating along with the effects of movie characteristics.

Since ratings are submitted on a 10-point scale, we model posted movie ratings as follows:

$$\Pr(R_{ijt} = r \mid z_{ijt} = 1) = \Pr(\kappa_{r-1} < R^*_{ijt} < \kappa_r), \quad \text{where } r = 1, 2, \ldots, 10. \qquad (3)$$

The variable R_{ijt} is the rating submitted by i for movie j at time t. The condition $z_{ijt} = 1$ indicates that a rating is posted (and $z_{ijt} = 0$ otherwise) and κ_r are cut points for rating categories.[2]

[2] Rating scheme is fixed for all movies, and therefore the thresholds are the same for all movies (Williams 2006).

4.2. Rating Selection (Incidence) Model

Prior studies develop a model of user rating incidence to describe whether or not to rate a product (Ying et al. 2006, Moe and Schweidel 2012). In particular, they assume an individual's decision to submit a product rating is a function of four components: (1) experience with the product, (2) varying baseline tendencies to submit ratings, (3) the current state of the rating environment at the time of the rating, and (4) post-purchase evaluation. However, our main interest lies in correctly estimating the social effects. As such, rather than largely focusing on the selection process, we specify a rating incidence model in order to mainly control for the effect of self-selection decisions of users posting on the social movie site in our rating response model estimation. In (4), we conceptualize a latent component of rating submission tendency as a poster's individual and movie specific constructs. Individual i submits a rating for movie j at time t if

$$U^*_{ijt} = \delta_{i0} + \delta_{1:n_3} X_i + \omega_{1:n_4} Z_{jt(i)} + u_{ijt} > 0, \quad \text{where } \delta_{i0} \sim \mathrm{N}(\alpha_2, \sigma^2_{\delta_0}). \tag{4}$$

The term u_{ijt} is an idiosyncratic error and $u_{ijt} \sim \mathrm{N}(0, 1)$. The varying baseline tendency δ_{i0} allows for variation across individuals in their baseline propensities to submit product ratings. This term has a normal distribution with a mean of α_2 and a standard deviation of σ_{δ_0}. Then, the probability that i contributes a rating for movie j at time t is given by the following probit model:

$$\Pr(z_{ijt} = 1) = \Phi(\delta_{i0} + \delta_{1:n_3} X_i + \omega_{1:n_4} Z_{jt(i)}), \tag{5}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function (c.d.f.). The vectors $\delta_{1:n_3}$ and $\omega_{1:n_4}$ capture the effects of covariates characterizing the poster's characteristics and the movie's ratings environment on the incidence decision, respectively (Moe and Schweidel 2012; the selection effect).

4.3. Posting a Rating for a Specific Movie

Whereas our rating model (3) can be used to predict poster i's rating for movie j at time t, the poster's decision to submit a rating and her value of rating are not independent of each other (Ying et al. 2006). As such, a two-stage ratings provision process can be represented based on whether to rate a movie (5) and what to rate the movie (3). Thus, the expected post-movie evaluation is

$$\begin{aligned} E[R^*_{ijt} \mid z_{ijt} = 1] &= E[R^*_{ijt} \mid U^*_{ijt} > 0] \\ &= E[\beta_{i0} + \beta_{1:n_1} X_i + \gamma_{j0} + \gamma_{1:n_2} Z_{jt(i)} + \varepsilon_{ijt} \mid \delta_{i0} \\ &\qquad + \delta_{1:n_3} X_i + \omega_{1:n_4} Z_{jt(i)} + u_{ijt} > 0] \\ &= \beta_{i0} + \beta_{1:n_1} X_i + \gamma_{j0} + \gamma_{1:n_2} Z_{jt(i)} \\ &\qquad + E[\varepsilon_{ijt} \mid u_{ijt} > -(\delta_{i0} + \delta_{1:n_3} X_i + \omega_{1:n_4} Z_{jt(i)})]. \end{aligned} \tag{6}$$

If the errors ε_{ijt} and u_{ijt} are correlated with each other, our estimates in (3) are spurious and we need to account for the selection process. Following the Heckman correction (Heckman 1979),

$$E[\varepsilon_{ijt} \mid u_{ijt} > -(\delta_{i0} + \delta_{1:n_3} X_i + \omega_{1:n_4} Z_{jt(i)})] = \rho \sigma_\varepsilon \lambda_{ijt}, \quad \text{where } \rho = \mathrm{corr}(\varepsilon_{ijt}, u_{ijt}) \text{ and}$$

$$\lambda_{ijt} = \frac{\phi(\delta_{i0} + \delta_{1:n_3} X_i + \omega_{1:n_4} Z_{jt(i)})}{\Phi(\delta_{i0} + \delta_{1:n_3} X_i + \omega_{1:n_4} Z_{jt(i)})}. \tag{7}$$

First, for each rating observation in the selected sample, we can now compute

$$\hat{\lambda}_{ijt} = \frac{\phi(\hat{\delta}_{i0} + \hat{\delta}_{1:n_3} X_i + \hat{\omega}_{1:n_4} Z_{jt(i)})}{\Phi(\hat{\delta}_{i0} + \hat{\delta}_{1:n_3} X_i + \hat{\omega}_{1:n_4} Z_{jt(i)})}$$

(the inverse Mill's ratio) by estimating the selection Equation (5) (probit model) by maximum likelihood estimation (MLE). Second, we fit the proposed rating response model (3) with the revised Equation (2) as

$$\begin{aligned} R^*_{ijt} &= \beta_{i0} + \beta_{1:n_1} X_i + \gamma_{j0} + \gamma_{1:n_2} Z_{jt(i)} \\ &\qquad + \rho_1 \hat{\lambda}_{ijt} + \rho_2 \hat{\lambda}^2_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{8}$$

to take account of the selection effect and its nonlinear relationship with the rating response (Moe and Schweidel 2012).

4.4. Addressing the Reflection Problem in Estimation

The other key issue in studies attempting to identify social influence is the reflection problem (Manski 1993). The reflection problem in our context is that users choose similar ratings for a movie, not because of the influence of others' rating but because they are in the same reference group as others. That is, users tend to behave similarly because they are alike or face a common environment. For example, users who watch and rate documentaries may have inherently similar preferences. Thus, the relationship between observational learning and individual rating outcome could be spurious. The parameter estimates for observational learning variables are biased by the endogeneity stemming from this problem.

Following Bramoullé et al. (2009), who suggest ways to identify the true effect of social influence by accounting for the reflection problem, we first consider unobservable variables common to the individuals that belong to the same affiliated (not friendship) network structure for a movie. γ_{j0} in (1) captures not only variation across movies but also a movie fixed unobservable that has a common effect on the rating outcomes of all posters within the movie j's affiliation network (e.g., individuals' similar preferences of watching and reviewing the movie). Then, the effect of the social influence may not be correctly identified if γ_{j0} is correlated with the precedent posters' ratings information. Using a movie's group means of the variables and subtracting corresponding group means from the variables, we can eliminate γ_{j0} because $\gamma_{j0} - \bar{\gamma}_{j0} = 0$ within the movie. Hence, the differencing equation for (8) is

$$(R^*_{ijt} - \bar{R}^*_j) = (V_{ij} - \bar{V}_j) + \gamma_{1:n_2}(Z_{jt(i)} - \bar{Z}_j) + \rho_1(\hat{\lambda}_{ijt} - \bar{\hat{\lambda}}_j) + \rho_2(\hat{\lambda}^2_{ijt} - \bar{\hat{\lambda}}^2_j) + (\varepsilon_{ijt} - \bar{\varepsilon}_j), \tag{9}$$

and we can rewrite (9) with (1) as

$$\Delta R^*_{ijt} = \Delta\beta_{i0} + \beta_{1:n_1}\Delta X_i + \gamma_{1:n_2}\Delta Z_{jt(i)} + \rho_1\Delta\hat{\lambda}_{ijt} + \rho_2\Delta\hat{\lambda}^2_{ijt} + \Delta\varepsilon_{ijt}, \quad \text{where } \Delta y_{ij} = y_{ij} - \bar{y}_j. \tag{10}$$

Now, the movie's network fixed effects γ_{j0} is cancelled out. Therefore, the model generates internal conditions that ensure identification of social effects in spite of serial correlation of $\Delta\varepsilon_{ijt}$ (Bramoullé et al. 2009).

Then, (3) for posted movie ratings becomes

$$\Pr(R_{ijt} = r \mid z_{ijt} = 1) = \Pr(\Delta\kappa_{r-1} < \Delta R^*_{ijt} < \Delta\kappa_r), \quad \text{where } r = 1, 2, \ldots, 10. \tag{11}$$

Under the assumption that $\Delta\varepsilon_{ijt} \sim \mathrm{N}(0,1)$, the probability with which an r-star rating is posted is represented by the following ordered probit specification:

$$\Pr(R_{ijt} = r \mid z_{ijt} = 1) = \begin{cases} \Phi(-\Delta R^*_{ijt}), & r = 1; \\ \Phi(\Delta\kappa_1 - \Delta R^*_{ijt}) - \Phi(-\Delta R^*_{ijt}), & r = 2; \\ \Phi(\Delta\kappa_2 - \Delta R^*_{ijt}) - \Phi(\Delta\kappa_1 - \Delta R^*_{ijt}), & r = 3; \\ \Phi(\Delta\kappa_3 - \Delta R^*_{ijt}) - \Phi(\Delta\kappa_2 - \Delta R^*_{ijt}), & r = 4; \\ \vdots & \vdots \\ 1 - \Phi(\Delta\kappa_8 - \Delta R^*_{ijt}), & r = 10, \end{cases} \tag{12}$$

where $\Delta\kappa_r = \kappa_r - \bar{\kappa}_{r(j)}$ are differenced cut points by using average cut points of a movie for the ordered probit model, and $\Phi(\cdot)$ denotes the standard normal c.d.f.

To estimate the parameters in (5) and (12) with the random effects for variation across individuals, we use the two-level mixed-effects estimation for the probit model and the ordered probit model, respectively. This allows for heterogeneity across posters, as well as considers the correlation that may exist among the rating occurrence level variation and poster level variation.

5. Results

5.1. Selection Model Estimation Results

Valence, variance, and volume of posted product ratings are widely used metrics in the ratings literature (Dellarocas and Narayan 2006). Using these metrics in a rating incidence model, Moe and Schweidel (2012) found that consumers are more likely to post an opinion when the ratings already posted are more positive and disagreeable. In addition to these metrics, we specify individual poster constructs such as gender, age, online community membership information, review history, and online friend network in the community because such individual characteristics can directly influence posters' decision to submit a rating. We also include cumulative advertising spending on the movie and its cumulative box office sales as proxies for general interest in the market and as additional constructs for the rating environment with respect to movies.

Table 4 shows the results of the mean effects and random effects from our rating selection model estimation using multilevel mixed-effects probit regression. *Valence* is the current weekly average rating of a movie and *Variance* is the current weekly variance of ratings for the movie. *Volume* is the current cumulative number of ratings in the week. Mainly, the effects of the three rating environmental variables confirm the findings in Moe and Schweidel (2012), which suggest individuals are more likely to post an opinion

Table 4 Estimates of Individual Characteristics and Rating Environment Effects on Selection

	Estimate	S.E. (robust)
Individual constructs		
δ_0	-1.0486^{***}	(0.0302)
δ_1 *Gender*	0.0019^{-}	(0.0010)
δ_2 *Age*	-0.0003^{***}	(0.0000)
δ_3 Log[*DaysofMembership*]	-0.0269^{***}	(0.0026)
δ_4 Log[*ProfileViews*]	-0.0012^{*}	(0.0005)
δ_5 Log[*Num.ofFriends*]	0.0002	(0.0006)
δ_6 Log[*Num.ofRatings*]	0.0007	(0.0005)
δ_7 Log[*Num.ofReviews*]	0.0064^{***}	(0.0005)
Rating environment constructs		
ω_1 *Valence*	0.0206^{***}	(0.0028)
ω_2 *Volume*	-0.0684^{***}	(0.0020)
ω_3 *Variance*	0.0061^{***}	(0.0016)
ω_4 Log[*Cum.Ad-Spending*]	-0.1615^{***}	(0.0066)
ω_5 Log[*Cum.Ad-Spending*]^2	-0.0287^{***}	(0.0018)
ω_6 Log[*Cum.BoxOfficeSales*]	0.0853^{***}	(0.0030)
ω_7 *Weeks*	-0.0887^{***}	(0.0011)
Variation of baseline tendency		
$\sigma^2_{\delta_0}$	4.69E−19	(6.50E−13)
Number of posters	20,336	
Number of observations	584,943	
VIF	2.95	
Log-likelihood	−134,858.59	

Note. Standard errors in parentheses.
$^{*}p < 0.05$; $^{***}p < 0.001$; $^{-}p < 0.1$.

when the ratings already posted are more positive ($\omega_1 > 0$) and more disagreeable ($\omega_3 > 0$).

In addition, our results can enrich the explanation of consumer propensity of posting with respect to user online characteristics and the movie's current general awareness level. First, the propensity of posting becomes higher if a consumer is younger or newer in the online community (δ_2, δ_3 and $\delta_4 < 0$). In contrast, a user who has posted more text reviews in the online community is more likely to post an opinion ($\delta_7 > 0$) although the frequency of posting numerical ratings has no significant effect. Second, advertising spending has a negative effect and its relationship is nonlinear (ω_4 and $\omega_5 < 0$ and highly significant), which indicates the consumer propensity of posting becomes lower when the overall awareness level of a movie increases by marketing efforts. In other words, consumers' willingness to post their opinions (generating social media) in order to inform other consumers becomes lower if the general awareness of the movie among consumers is already high. As such, consumers are more likely to post their opinions when quality information provided by the producer is sparse. Also, if a movie is more successful, consumers are more likely to post an opinion about the movie ($\omega_6 > 0$).

5.2. Rating Model Estimation Results

5.2.1. Individual Heterogeneity and the Relationship Between Ratings Incidence and Decision. Table 5 shows the results of the mean effects and random effects from our rating model estimation using multilevel mixed-effects ordered probit regression. The column labeled "Model 1" in Table 5 runs the regression based on all observations and the column labeled "Model 2" uses only those observations that have *FRWOM* as well as *CROWDRA*, i.e., only those rating instances in which a prior friend and crowd rating exist. The estimate of variation of baseline positivity ($\sigma^2_{\beta_0}$) shows considerable heterogeneity across individuals in their ratings.

In addition to variation in the baseline positivity (or negativity), we find that an individual poster's posting decision is significantly correlated with R^*_{ijt}, which is captured by the parameters ρ_1 and ρ_2. The observation that $\hat{\rho}_1 > 0$ and $\hat{\rho}_2 < 0$ in Model 1 suggests that individuals with high propensity to post would be more likely to provide higher product ratings but the relationship is not monotonic. This finding demonstrates the potentially nonlinear relationship between the ratings incidence and decision, consistent with empirical findings in the literature.[3]

5.2.2. Herding vs. Differentiation. In our model, the influence of others' ratings on a user's post-movie evaluation R^*_{ijt} is measured by four factors: *CROWDRA*, *FRWOM*, *Vol-CROWDRA*, and *Vol-FRWOM* (coefficients γ's in Table 5). In the following, we investigate how the marginal effects of *CROWDRA* and *FRWOM* are moderated by the popularity of a movie (measured by *Vol-CROWDRA*) and social interaction (*Vol-FRWOM*).[4]

The impact of movie popularity on the effect of crowd ratings in the absence of social interaction.[5] Table 5 shows that the effect of *CROWDRA* becomes more positive as *Vol-CROWDRA* increases ($\gamma_5 > 0$ and statistically significant at the 0.001 level) in Model 1. To show how the marginal effect of *CROWDRA* varies when *Vol-CROWDRA* is at its lowest and highest values, we present the marginal effect plots in Figure 3 using parameter estimates in Model 1 of Table 5 based on the Berry et al. (2012) guideline. Figure 3(a) illustrates that the marginal effect of *CROWDRA* becomes negative and statistically significant when ΔLog[*Vol-CROWDRA*] is less than about -0.5, whereas the positive and statistically significant marginal effect is found when ΔLog[*Vol-CROWDRA*] is greater than 0.25. Figure 3(b) shows a similar, though insignificant, pattern for Model 2. This suggests that posters tend to lower their rating when fewer precedent posters have generated more positive ratings, i.e., the differentiation effect emerges. However, herding of subsequent ratings can also exist when a considerably large number of posters have generated more positive ratings. Therefore, consistent with Hypothesis 1, we conclude that the social influence of prior ratings by the community depends on whether the associated movie is a popular one or not. Although prior theory suggests that differentiation behavior may be more salient for niche items than mainstream ones (Berger and Heath 2008), most prior studies on social influence in ratings have tended to focus on aggregate behavior and have thus missed these differences based on movie popularity.

The impact of social interaction on the effect of friends ratings. The estimates of γ_9 and γ_{10} in Table 5 are both positive and γ_9 is statistically significant at the 0.0001 level. Thus, the marginal effect of *FRWOM* at different values of *Vol-FRWOM* can be considered positive and statistically significant because of the significant main effect of *FRWOM* ($\gamma_8 > 0$ and statistically significant at the 0.0001 level). To illustrate whether the marginal effect of *FRWOM* is consistently positive as *Vol-CROWDRA* increases or decreases as

[3] Moe and Schweidel (2012) showed the scenario where individuals with extreme post-purchase evaluations are more likely to participate in rating submissions.

[4] Note that we do not interpret the main effects (γ_1 and γ_8) because *CROWDRA* and *FRWOM* do not exist if *Vol-CROWDRA* $= 0$.

[5] Here we single out the impact of movie popularity by assuming no social interaction, i.e., *Vol-FRWOM* $= 0$.

Table 5 Estimates of Social Influence Effects on Rating

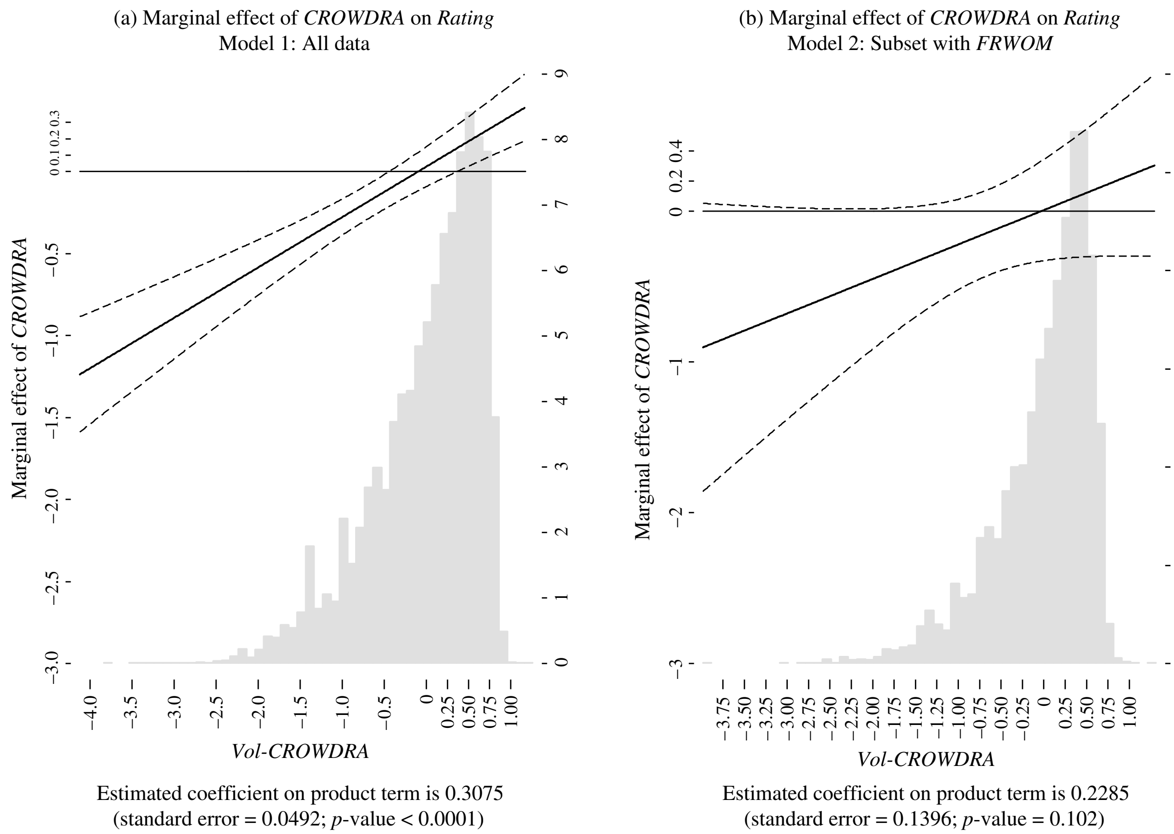
	Model 1		Model 2	
	Estimate	S.E (robust)	Estimate	S.E (robust)
Individual constructs				
β_1 Δ*Gender*	−0.3067***	(0.0167)	−0.3615***	(0.0379)
β_2 Δ*Age*	−0.0091***	(0.0009)	−0.0077***	(0.0020)
β_3 ΔLog[*DaysofMembership*]	−0.2115***	(0.0334)	−0.2318**	(0.0741)
β_4 ΔLog[*ProfileViews*]	0.0505***	(0.0077)	−0.0041	(0.0192)
β_5 ΔLog[*Num.ofFriends*]	0.0817***	(0.0095)	0.1780***	(0.0232)
β_6 ΔLog[*Num.ofRatings*]	−0.0645***	(0.0080)	−0.0537**	(0.0175)
β_7 ΔLog[*Num.ofReviews*]	−0.0611***	(0.0072)	−0.0692***	(0.0177)
Social influence constructs				
γ_1 Δ*CROWDRA*	0.0309	(0.0620)	0.0078	(0.1713)
γ_2 Δ*Vol-FRWOM*	0.0035	(0.0041)	0.0089⁻	(0.0053)
γ_3 ΔLog[*Vol-CROWDRA*]	−0.2094***	(0.0262)	0.0150	(0.0720)
γ_4 Δ*CROWDRA* $\times$ Δ*Vol-FRWOM*	−0.0537	(0.0391)	−0.0919	(0.0573)
γ_5 Δ*CROWDRA* $\times$ ΔLog[*Vol-CROWDRA*]	0.3075***	(0.0492)	0.2285⁻	(0.1396)
γ_6 Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.0087	(0.0086)	0.0011	(0.0136)
γ_7 Δ*CROWDRA* $\times$ Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.0912**	(0.0342)	0.1098*	(0.0478)
γ_8 Δ*FRWOM*	—		0.1804***	(0.0123)
γ_9 Δ*FRWOM* $\times$ Δ*Vol-FRWOM*	—		0.0296***	(0.0056)
γ_{10} Δ*FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	—		0.0165	(0.0207)
γ_{11} Δ*FRWOM* $\times$ Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	—		0.0045	(0.0113)
Movie constructs				
γ_{12} ΔLog[*Cum.Ad-Spending*]	−0.2053***	(0.0482)	0.0181	(0.1146)
γ_{13} ΔLog[*Cum.Ad-Spending*]^2	−0.1271***	(0.0118)	−0.1210***	(0.0252)
γ_{14} ΔLog[*Cum.BoxOfficeSales*]	0.2283***	(0.0254)	−0.0713	(0.0744)
Selection effects				
$\rho_1 \Delta\hat{\lambda}_{ijt}$	0.9740***	(0.3059)	0.5613	(0.6782)
$\rho_2 \Delta\hat{\lambda}^2_{ijt}$	−0.2032**	(0.0714)	−0.1483	(0.1543)
Variation of baseline positivity (negativity)				
$\sigma^2_{\beta_0}$	0.4901	(0.0246)	0.4672	(0.0463)
Number of posters	20,309		3,913	
Number of observations	40,760		8,780	
VIF	3.35		3.31	
Log-likelihood	−77,624.881		−16,104.143	

Notes. Standard errors in parentheses. *CROWDRA*, Log[*Vol-CROWDRA*], and Log[*Cum.Ad-Spending*] are mean centered to reduce multicollinearity. The estimates of $\Delta\kappa$'s are not reported here because of page limits.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; $^-p < 0.1$.

we hypothesized, Figure 4(a) plots the marginal effect of *FRWOM* at different values of *Vol-CROWDRA* in Model 2. For the values of *Vol-CROWDRA* that fall between the 5th and 100th percentiles, the marginal effect of *FRWOM* is positive and statistically significant and the magnitude remains almost unchanged. That is, there is always herding with friends' ratings for a movie regardless of its popularity. This may be because friends have similar preferences or because they influence one another. Interestingly, this herding behavior becomes stronger as more friends have provided ratings for the movie, as shown in Figure 4(b). This suggests that the effect may be tied to more than just similarity among friends. Increases in social signals from friends may facilitate herding behavior among friends. Further, cascading by the crowd does not affect the herding in friends ratings. In other words, within a friendship network reviewing a particular movie, an individual poster within the network tends to follow opinions generated by friends in the network, although this poster can show differentiation behavior relative to opinions of the crowd.

The impact of social interaction on crowd ratings ignoring movie popularity. The estimates of γ_4 in Models 1 and 2 of Table 5 are negative but statistically insignificant. To assess any change in the effect of *CROWDRA*, Figure 5 illustrates the varying marginal effect at different values of *Vol-FRWOM*. Figure 5(a) (Figure 5(b)) shows that the marginal effect of *CROWDRA* is negative as *Vol-FRWOM* becomes greater in Model 1 (Model 2). That is, increases in the volume of prior friend ratings for a movie can moderate the effect of *CROWDRA*, which could be either negative or positive. However, the marginal effect of *CROWDRA* given *Vol-FRWOM* is statistically insignificant in the plots.

Figure 3 Marginal Effect Plots to Evaluate Herding or Differentiation in Crowd Ratings

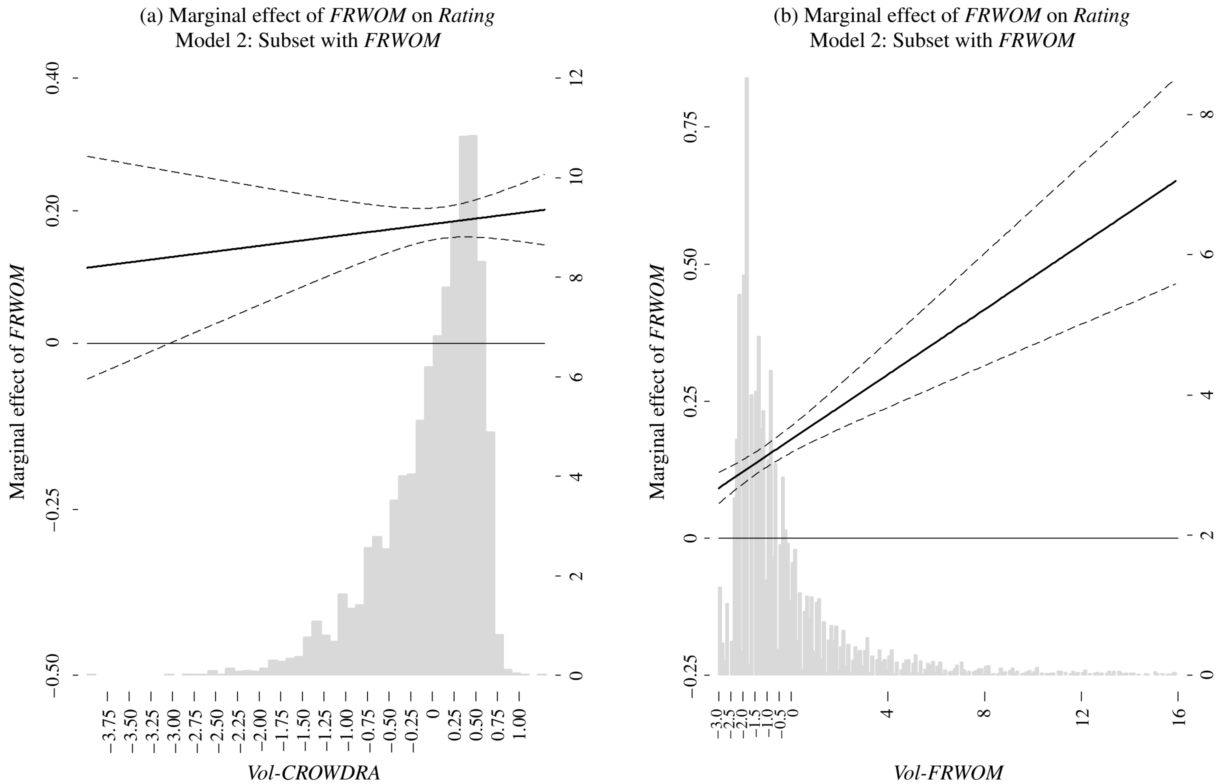


Notes. The vertical axes on the left indicate the magnitude of the marginal effect. The vertical axes on the right are for the histogram, which plots the distribution of observations in the sample on *Vol-CROWDRA* depicted on the horizontal axis. The solid line is the computed marginal effects given different values of *Vol-CROWDRA* and dashed lines are upper and lower limits of 95% confidence intervals of the marginal effects.

The joint moderation effect of movie popularity and social interaction on the effect of crowd ratings. We have earlier examined the impact of movie popularity and social interaction separately, ignoring the plausible interaction between them. In Table 5, we find that the estimated parameter (γ_7) for the three-way interaction term, i.e., Δ*CROWDRA* $\times$ Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*], is positive and statistically significant at less than 0.03 level in both models. Thus, social interaction (*Vol-FRWOM*) and movie popularity (*Vol-CROWDRA*) jointly moderate the effect of *CROWDRA* on rating. The plots in Figure 6 illustrate the marginal effects of *CROWDRA* (represented by simple slopes) on rating for all values of *Vol-FRWOM* (the level of social interaction) for four illustrative values (25th, 50th, 75th, and 95th percentiles) of *Vol-CROWDRA* (movie popularity). Stars are placed when the marginal effect is statistically significant at the 0.05 level. As Figure 6(a) shows, for extremely popular movies (e.g., the line with the 95th percentile of *Vol-CROWDRA*), social interaction (higher *Vol-FRWOM*) acts to increase the marginal effect of *CROWDRA*, or leads to more herding. However, for most movies, the herding effect diminishes as more friends ratings become available; and for unpopular movies, users are more likely to differentiate.

Whereas Model 1 includes the whole population of users, Model 2 focuses on the subset of users who have a social network at the time of posting a rating. Figure 6(b) shows herding at low, but differentiation at high, levels of social interaction. Different from Figure 6(a), increased social interaction prompts users to change from herding to differentiation more quickly if the movie is more popular. A popular movie can exhibit both herding and differentiation behavior of users, depending on the extent of social interaction. We can conceptualize *Vol-FRWOM* as an in-degree measure (Wasserman and Faust 1994) for a user within a movie's social network. Thus, as more friend opinions flow in, differentiation behavior against the crowd opinion can becomes stronger, whereas the herding effect of the crowd rating becomes weaker, if herding exists (such as for popular movies). In other words, the influence from the user's immediate social network reduces the influence of the broader population.

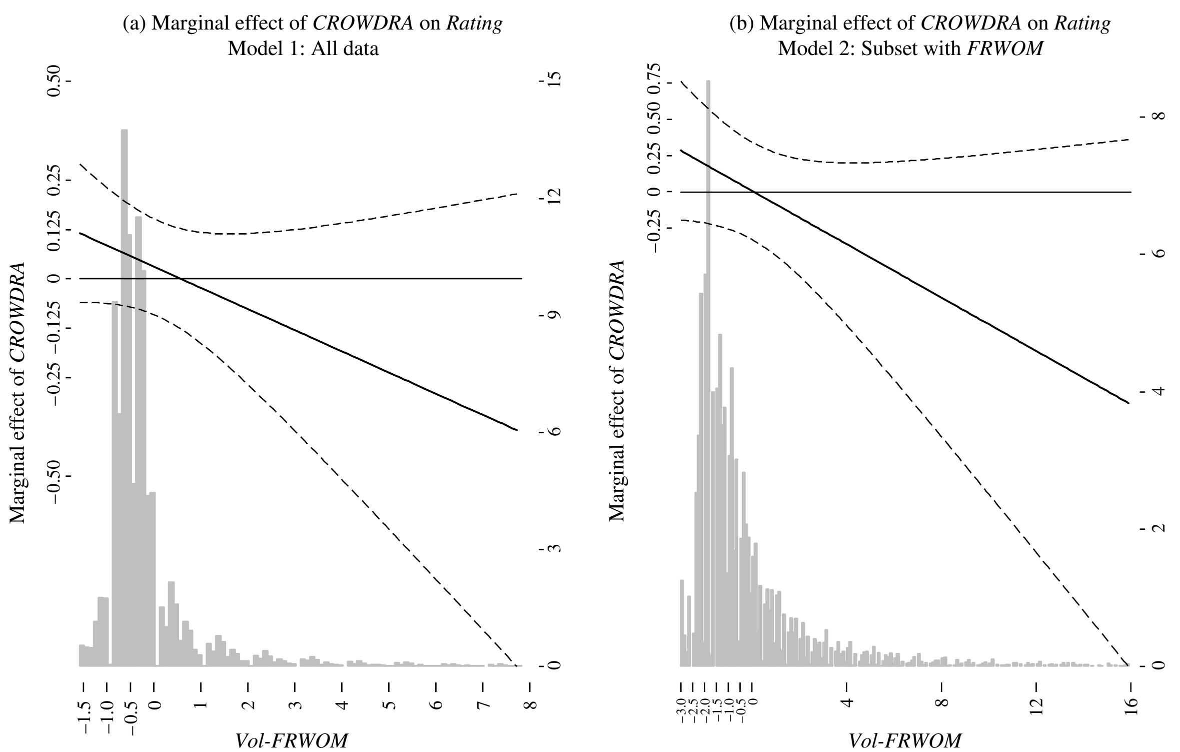
Figure 4 Marginal Effect Plots to Evaluate Herding in Friends Ratings



Estimated coefficient on product term is 0.0165 (standard error = 0.0207; *p*-value = 0.4230)

Estimated coefficient on product term is 0.0296 (standard error = 0.0056; *p*-value = 0.0000)

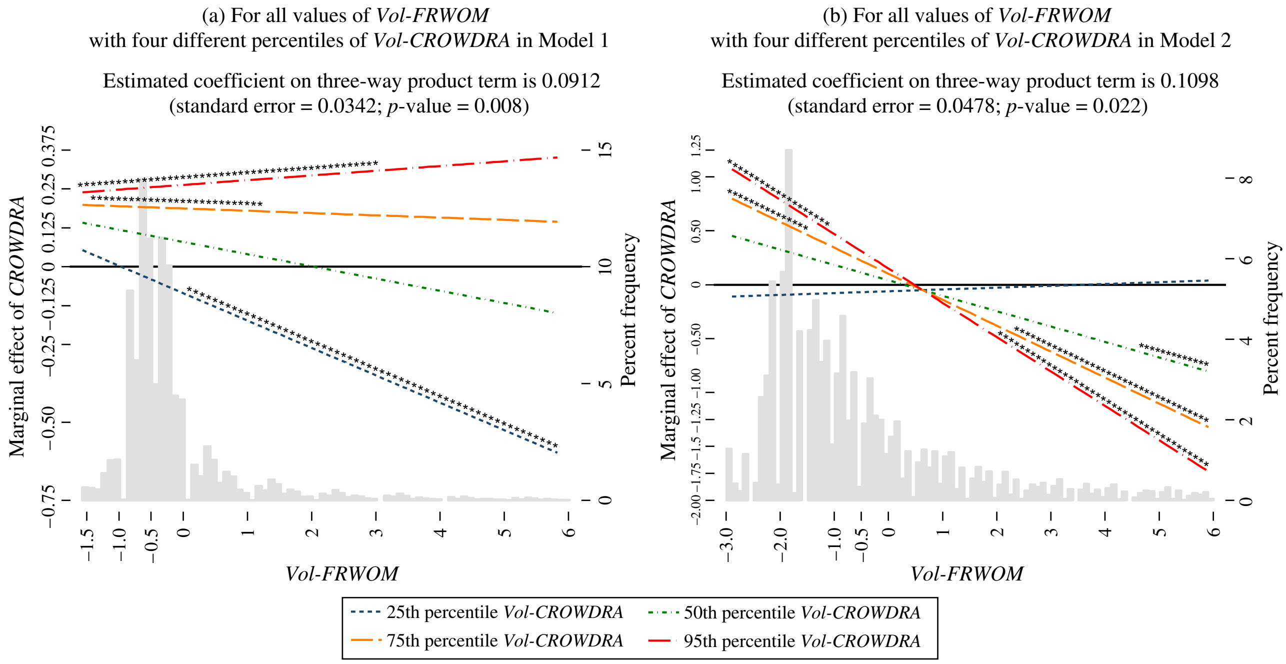
Figure 5 Marginal Effect Plots to Evaluate the Impact of Social Interaction on the Effect of Crowd Ratings



Estimated coefficient on product term is −0.0537 (standard error = 0.0391; *p*-value = 0.170)

Estimated coefficient on product term is −0.0919 (standard error = 0.0573; *p*-value = 0.108)

Figure 6 **(Color online) Marginal Effect Plots to Evaluate the Jointly Moderating Effect of Social Interaction and Movie Popularity on the Effect of Crowd Ratings**



5.3. The Role of Social Pressure

Based on estimated β's for user characteristics variables in Table 5, males tend to generate lower ratings than females. Younger users choose higher ratings. More interestingly, the intensity of a user's online activity on the social movie site is negatively related to the user's rating. For example, if a user has longer membership duration (*DaysofMembership*) or a large number of numerical or text reviews (*Num.ofRatings* or *Num.ofReviews*) on the social movie site, she is more likely to choose a lower rating (β_3, β_6, and $\beta_7 < 0$ and significant in both models). Therefore, as expected, more experienced users tend to have lower ratings.

Interestingly, an increase in a user's visibility, measured by the number of her profile page views by others (*ProfileViews*), is associated with an increase in the user's rating ($\beta_4 > 0$ and significant in Model 1 of Table 5). *Num.ofFriends* is another measure for the level of social involvement with friends in the online community. It consistently shows a positive effect of social involvement as hypothesized ($\beta_5 > 0$ and significant in Table 5). By measuring a user's level of social involvement (specifically, users who anticipate their ratings will be widely consumed by others) on the social movie site with *ProfileViews* and *Num.ofFriends*, we confirm that users with a higher level of social involvement tend to provide more positive ratings for movies.

Our estimations so far assume that the parameters are the same at all rating categories (e.g., each value in a 1–10 star scale). We can relax this parallel line assumption (i.e., the parameters do not vary with rating categories), to examine any varying effects of the social pressure variables. Brant tests indicate that some user characteristic variables do violate the parallel line assumption. Therefore, we reestimated Model (1) using generalized ordered logistic regression, which allows the parameters to vary according to rating categories by a series of binary logistic regressions.[6] Based on the results, a user's activity level in the community represented by *DaysofMembership*, *Num.ofRatings*, and *Num.ofReviews* has stronger negative effect at more positive rating categories. In other words, highly active users in the online community generally tend not to choose very positive ratings. For example, when a highly active user contrasts nine stars with a rating value below nine stars, the user is more likely to choose a value that is less than nine stars. Hence, a user's negative rating attitude becomes greater with very positive rating levels if the user has been very active in the online community. Also, the negative rating attitude becomes lesser or even opposite if a very active user contrasts her rating with a very negative rating level. As a result, highly active posters tend not to choose a very positive or very negative rating value.

5.4. Robustness Check

A key data limitation in our study is the lack of information on each user's timing of friendship formation

[6] The results of estimation with generalize ordered logit regression are not reported here to save space. They are available upon request.

Table 6 Estimates of Social Influence Effects on Rating for Each Quarter of 2007

Social influence constructs	All	Q4	Q3	Q2	Q1
		Model 1 estimates			
γ_1 Δ*CROWDRA*	0.0309	0.2024	0.2706*	0.1702	0.0130
γ_2 Δ*Vol-FRWOM*	0.0035	−0.0037	0.0084	−0.0029	−0.0358***
γ_3 ΔLog[*Vol-CROWDRA*]	−0.2094***	−0.3600***	−0.3335***	−0.0325	−0.1720**
γ_4 Δ*CROWDRA* $\times$ Δ*Vol-FRWOM*	−0.0537	0.0555	−0.0153	−0.0916	−0.0173
γ_5 Δ*CROWDRA* $\times$ ΔLog[*Vol-CROWDRA*]	0.3075***	0.2657**	0.4234***	0.2712*	0.3908**
γ_6 Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.0087	−0.0217	0.0031	0.0066	0.0511**
γ_7 Δ*CROWDRA* $\times$ Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.0912**	0.2158**	0.2145*	0.0098	−0.1404
Number of posters	20,309	5,452	8,022	8,304	2,945
Number of observations	40,760	8,080	13,318	13,675	5,156
		Model 2 estimates			
γ_1 Δ*CROWDRA*	0.0078	0.6215	0.1776	0.0347	−0.0720
γ_2 Δ*Vol-FRWOM*	0.0089⁻	−0.0092	0.0124⁻	0.0029	0.0023
γ_3 ΔLog[*Vol-CROWDRA*]	0.0150	−0.1157	−0.5269**	0.2258	0.0918
γ_4 Δ*CROWDRA* $\times$ Δ*Vol-FRWOM*	−0.0919	0.0186	−0.0588	−0.0201	−0.2855⁻
γ_5 Δ*CROWDRA* $\times$ ΔLog[*Vol-CROWDRA*]	0.2285	0.4829⁻	0.8920*	0.0584	−0.8397*
γ_6 Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.0011	−0.0284	−0.0100	0.0320	−0.0213
γ_7 Δ*CROWDRA* $\times$ Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.1098*	0.1639	0.1767	0.0424	−0.0352
γ_8 Δ*FRWOM*	0.1804***	0.2017***	0.2312***	0.1959***	0.1785***
γ_9 Δ*FRWOM* $\times$ Δ*Vol-FRWOM*	0.0296***	0.0103	0.0564***	0.0316***	0.0257⁻
γ_{10} Δ*FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.0165	0.0497	−0.0322	0.0069	−0.0252
γ_{11} Δ*FRWOM* $\times$ Δ*Vol-FRWOM* $\times$ ΔLog[*Vol-CROWDRA*]	0.0045	−0.0154	−0.0428⁻	0.0335*	−0.0228
Number of posters	3,913	1,162	1,841	1,883	687
Number of observations	8,780	1,894	2,632	3,006	1,138

Notes. Standard errors in parentheses. Other estimates of are not reported here and qualitatively similar with the estimates in Table 5.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; $^{-}p < 0.1$.

in the online community. Because we could not capture when friendship ties were formed in our data, it is possible that a friendship tie was former after a user posted a review (and thus that user could not actually see prior ratings from the friend). Unless we capture the dynamics of friendship formulations, this can influence our results. Our data included movies released in 2007 and their user ratings posted within the first 16 weeks after release. Friendship data is based on data retrieved from November 25, 2008, through December 3, 2008. Therefore, posted ratings in the fourth quarter in 2007 is least likely to be affected by this data limitation because the latest possible time of friendship tie formation and the time of posting ratings in that quarter are quite close. For this reason, ratings in the first quarter of 2007 are most likely to be affected by this data limitation because the chance that the friendship ties were formed much later in the year is higher. Hence, we provide estimation results for each quarter of 2007 in Table 6 as a robustness check to ensure that there is no systematic bias introduced in the results because of this limitation.

The results of Model 1 for the third and fourth quarters in Table 6 are qualitatively similar to the results for the entire data. This suggests that our hypotheses are still supported by the results for the quarters that are least likely to be affected by the limitation. As we expected, the results in the first and second quarters in Table 6 show some changes that may be due to the limitation. Similarly, the results of Model 2 for the third and fourth quarters in Table 6 are also qualitatively similar to the previous results. Thus, the timing of friendship ties does not seem to be driving our findings.

6. Discussion and Conclusions

Recent research has started to establish that a user's online rating for a product may be influenced by prior ratings for that product submitted by other community members. This study adds to this emerging stream and further shows that the nature of the influence varies based on whether prior ratings are by friends or the crowd. Specifically, we find that a user's movie rating tends to be differentiated from past crowd ratings for niche movies and herd with the crowd for popular movies. In contrast, user ratings always herd with friend ratings independent of movie popularity. Further, herding with the crowd reduces as user interaction with friends increases. These results are summarized in Table 7.

The presence of observational learning in online user ratings lowers the quality of the review information created by users since each user rating would be associated with some degree of bias due to herding

Table 7 Summary of Findings from Social Influence Analysis

Rating types			Movie popularity: Popular	Movie popularity: Nonpopular
With crowd ratings				
	Social interactions	Low	Herding (H1 supported)	Differentiation (H1 supported)
		High	Lower herding (H3 supported)[a]	
With friend ratings			Herding (H2 supported)	

[a]Partially supported when popularity is not extremely high.

or differentiation behavior. The results have important implications for the design of rating systems. For example, many social media companies such as Yelp and Epinions implement models to detect and screen fraudulent consumer reviews but also rely heavily on large numbers of unbiased ratings to overcome the impact of a few fraudulent reviews. For example, Patty Smith, the director of corporate communications at Amazon, mentioned that "There's no way to vet the thousands of reviewers on Amazon. But we don't need to. When readers see 25 negative reviews and one glowing one—well, they can figure it out" (Luhn 2008). However, there may be biases due to which the opinion of the majority may not always provide true quality information. For example, if there is irrational herding in online reviews and behavioral biases among raters, a bias in early reviews can perpetuate, and such bias cannot easily be eliminated even with well-designed screening models.

Accordingly, our study points to two promising areas of research. The first is the need to develop statistical models that can take ratings data in the form of a time series and infer the "true" or unbiased assessment of a product's quality. Such a model would have application beyond de-biasing rating systems given recent research that show the existence of similar path dependence in a number of online systems, ranging from recommender systems (Fleder and Hosanagar 2009) to search engine ranking mechanisms (Cho and Roy 2004). A second research opportunity is in the design of user interfaces and systems that help users escape rating biases. Design approaches can range from educating users about their bias prior to submitting a rating to making the crowd ratings less prominent at the time a user is about to submit a rating.

From a practitioner's perspective, we believe that social media firms should invest in approaches to alleviate this bias. One potential step may be to encourage users to share their product experiences beyond just a numerical rating. Detailed reviews can help provide more information and context to subsequent users and can moderate the possible herding behavior. However, information overload and online anonymity can make such information flow difficult. Hence, detailed text reviews alone may not suffice. Our results suggest that the extent of herding is moderated considerably by reviews from friends. Increasing the visibility of friends' reviews and providing social media tools to allow users to interact may also be an effective way to prevent herding and reducing biases in online user reviews.

Acknowledgments

The authors thank the department editor, the associate editor, and the three anonymous reviewers for their constructive suggestions throughout the review process. The authors also thank the participants in the research seminars at University of Utah, Michigan State University, University of International Business and Economics, Beijing University of Posts and Telecommunications, University of Minnesota, Sichuan University, University of Denver, Rensselaer Polytechnic Institute, Southern Methodist University, University of Illinois at Chicago, Santa Clara University, Yahoo! Labs, Ulsan National Institute of Science and Technology, Fordham University, University of Memphis, Korea Advanced Institute of Science and Technology, and the Hong Kong University of Science and Technology for helpful comments and discussions. Yong Tan was supported in part by the National Natural Science Foundation of China [Grants 71231002 and 71328103].

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