Competing for Attention: An Empirical Study of Online Reviewers' Strategic Behaviors

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Abstract

Millions of web users are engaging in online communities such as blogs, online forums, or online review systems in order to interact with other people and to attract attention. However, attention is a scarce resource in the information-rich context. Online users have to adopt appropriate strategies in order to compete for attention. This study tries to understand how online users, especially online reviewers, compete for the scarce resource, attention, when writing online reviews. It theorizes the strategies used by online reviewers in choosing the right product and the right rating strategy when posting reviews so as to compete for attention. Using book reviews from Amazon and BarnesandNoble.com, we find that online reviewers do behave strategically in order to compete for scarce attention and enhance reputation. Their decisions are determined by the dynamic review environment at the time they review the product. In terms of product choice, the results suggest that reviewers are more likely to post reviews for popular but less crowded books so as to gain potential attention but reduce competition for attention at the same time. In terms of rating choice, reviewers with high reputation costs tend to be more conservative by adopting an imitation strategy more frequently than reviewers with low reputation costs. This is because although posting a differentiated rating can attract more attention, it usually brings more negative feedback since it deviates from the community consensus at that time period. Therefore, adopting a differentiation strategy may increase short term attention but could hurt a reviewer's long term reputation. This study tries to add to the growing literature on how social motivations drive online reviewers' behaviors.

Keyword:

Online attention, scarcity of attention, online product reviews, virtual community, user-generated content.

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INTRODUCTION

Online communities that offer user-generated content have experienced tremendous growth in the last few years. Among 18 million U.S. college students, 80% of them visit social networking sites on a regular basis (Williamson 2007). Websites such as Facebook, YouTube, and Amazon review systems, have attracted millions of users' attention. On the firm side, companies such as Starbucks, Electronic Arts, and Amazon, have built their own online communities to engage their customers and market their products. In 2008, U.S. ad spending on social networking sites reached $1.17 billion (Williamson 2009).

As online communities play an increasingly important role in companies' marketing strategies and in consumers' decision-making processes, it is critical to understand the incentives for individual users to contribute content to online communities. Previous studies on offline word-of-mouth (WOM) communication motives have shown that *altruism, product involvement, and self-enhancement* are the major motives for consumers to provide word-of-mouth (e.g. Dichter 1966, Sundaram et al. 1998). However, in the web-based online environment such as online review systems, reviewers become part of a virtual community through their contributions. Different from an offline environment, online reviewers are affiliated with the community which represents a social benefit to them (McWilliam 2000, Oliver 1999). Reviewers may contribute to online review systems to signify their participation and presence in the community and to receive *social benefits* such as attention, peer recognition, or reputation.

For individual users, the possibility of gaining social benefits such as attention is an important motivation for their contribution to online communities. For example, Peter Durward Harris, a top 10 Amazon reviewer, wrote specific guides to help other reviewers to write eye-catching reviews. Harris (2010) mentioned that reviewers tend to use the helpfulness vote as a proxy for the attention gained by their reviews, and reported that "every reviewer cares at least a little about votes", which "provide reviewers with reassurance that people are reading their reviews and assessing them". These statements are consistent with the findings from a survey study done by Hennig-Thurau et al. (2004), which demonstrated that gaining social benefits is the primary factor leading to online users' word-of-mouth behaviors. These statements are also consistent with the "attention economy" theory proposed by Goldhaber (1997), which stated that "obtaining attention is obtaining a kind of enduring wealth, a form of wealth that puts you in a preferred position to get anything this new economy offers".

Although online users desire to gain attention, it is not a trivial task since attention is arguably the most valuable and scarce resource on the Internet (Dahlberg 2005, Davenport and Beck 2001, Goldhaber 1997). The increasing amount of web content generated by online users creates a processing problem for users seeking relevant and useful information (Hansen and Haas 2001, Hunt and Newman 1997, Reuters 1998). With such a large supply of user-generated content, the scarce resource is not the information itself, but the limited attention that online users are able to allocate to online content (Ocasio 1997). Given the scarcity and value of attention, online users such as product reviewers are likely to compete for attention when contributing voluntarily to online communities.

There is a large body of literature on online product reviews. Most of the existing literature on online reviews has focused on the numerical aspects of reviews such as volume, valence, or variance, and the impact of reviews on consumers' purchases (e.g. e.g. Basuroy et al. 2003, Dellarocas et al. 2004, Liu 2006, Zhang et al. 2004). Some recent studies have begun to investigate the development and evolution of review ratings rather than their influence on sales (e.g. Godes and Silva 2009, Li and Hitt 2008, Moe and Trusov 2011). They examine the time trend of reviews, especially review ratings, and report that later ratings can be systematically different from early ratings.

However, virtually no attention has been paid to reviewers' social incentives and the effect of such social incentives. This paper extends the literature by investigating how social incentives such as how the desire for gaining attention drives online reviewers' review decisions and how online reviewers compete for attention. In particular, we study reviewers' decisions in two stages. First, at the product level, given the status of the current review environment, a reviewer decides whether or not to write a review for a particular product. Second, at the review level, a reviewer decides which rating to give based on the status of his or her online reputation.

We use a rich data set of online reviews of books and electronics collected from Amazon and BarnesandNoble.com (BN). The data is collected on a daily basis which allows us to replicate the review environment when reviewers make the review decisions. In addition, different from most of the prior studies which focus on one product category on one site, our data set allows us to compare across product categories and across different review systems.

Our results indicate that reviewers' review decisions are affected by social dynamics such as the existing review environment and reviewers' online reputation. In terms of product choice, at the population level, reviewers prefer to choose more popular but less crowded products to review, that is a product with high sales but few existing reviews. Popular products usually can attract more total attention so that reviewers are able to share from a large pie of attention.

Crowded review segments signal severe competition for attention. Therefore, by reviewing popular but uncrowded products, reviewers are able to gain more total attention and avoid competition for attention. In terms of the review ratings, the results suggest that differentiating reviews usually can attract more attention but are more likely to receive negative feedback than imitating reviews. Reviewers with high reputation costs tend to post close to average reviews to sustain their reputation. However, for reviewers with low reputation costs, they are more likely to differentiate from existing reviews in order to gain more attention.

Our comparison across two different review systems confirms that reviewers' behaviors to some extent are driven by the social mechanisms integrated into the website. When reviewers are able to quantify the social benefits, they are more motivated by these social incentives than when they cannot. We find that reviewers on Amazon, where a reviewer ranking system helps them to quantify their online reputation, become sensitive to the competition among existing reviews and tend to avoid crowded review segments. However, on the BN site, which does not include such social mechanisms, reviewers do not respond to the competition effect. Our findings yield interesting managerial implications for companies interested in encouraging online reviewers' contributions and monitoring their behaviors. We discuss the details in the last section and provide guidance for managers to better design their review systems for fulfilling different needs.

The rest of the paper is organized as follows. We first review the previous studies relevant to our research, and identify the gap in the existing literature that this study tries to fill. In the third section, we theorize how online reviewers compete for attention in two steps and develop our hypotheses. The fourth section presents the data and the empirical model used to test our hypotheses. The fifth section reports our empirical findings. Finally, we discuss the managerial implications in the sixth section.

LITERATURE REVIEW

With the increasing popularity of online user-generated content, there is a growing interest among academics in studying these online activities and their impact (e.g. Aggarwal et al. 2006, Aggarwal et al. 2007, Scoble and Israel 2006, Mayzlin 2006). For example, there is a large body of literature addressing the impact of online reviews on product sales (e.g. Basuroy et al. 2003, Dellarocas et al. 2004, Li and Hitt 2008, Zhang et al. 2004). These studies mainly use two measures to examine the impact of online reviews on product sales, which are *volume* and *valence* (e.g. Liu 2006, Zhang et al. 2004).

Volume measures the cumulative number of online reviews (e.g. Chevalier and Mayzlin 2006). A high volume of online reviews can increase the awareness of a product among potential buyers and therefore can potentially increase product sales (Liu 2006). Valence (or favorableness) measures the positive or negative nature of online reviews. Unlike volume, the impact from the valence of online reviews is mixed. For example, Liu (2006) and Duan et al. (2005) found that the valence of previous movie reviews does not have significant impact on later weekly box office revenues. However, Zhang and Dellarocas (2006) found a significant positive relationship between the valence of online reviews and box office revenues.

Researchers have recently started to investigate various factors that could influence online reviews such as the impact of online reviewers' characteristics (Forman et al. 2008), product types (Mudambi and Schuff 2010), previous review ratings (Moe and Trusov 2011), and product prices (Li and Hitt 2010). For example, Forman et al. (2008) considers the effect of reviewers' online identities on the impact of reviews. They report that reviews posted by real name reviewers will have a larger impact on product sales than those by anonymous reviewers. Li and Hitt (2010) model the price effects in the reviews and suggest that companies should consider such effects when developing optimal pricing strategies. Our study is part of this emerging research stream by considering the social motivations for reviewers to contribute to online review systems.

While understanding the consequences or the impact of web content is very important, it is also important to know how online users behave when they voluntarily contribute to these online communities. In the literature regarding member contributions in online communities, studies have found that when lacking direct monetary incentives, social incentives such as peer recognition and online reputation are important drivers for community members to contribute voluntarily (e.g. Lerner and Tirole 2002). For instance, in the open source software context, Lerner and Tirole (2002) shows that reputation and peer recognition are the primary motivations for users to contribute to the community in the absence of monetary rewards. Users' reputation signals their competence which drives them to contribute online. In the context of firm-hosted user communities, firm recognition of users' contributions is also reported as valuable to the users (Jeppesen and Frederiksen 2006). Positive reputation and peer recognition can motivate online users to keep contributing voluntarily (Pavlou and Gefen 2004, Resnick et al. 2000).

These theories and findings are applicable to online review communities where users' voluntary contributions are likely motivated by peer attention and online reputation. In a typical online review system, reviewers have to devote a substantial amount of time and efforts to write reviews. However, they typically do not get any direct monetary rewards for their contributions. This type of community is similar to the open source software development community as mentioned above. Consistently, Hennig-Thurau et al. (2004) reported that gaining social benefits is the most important motivator which encourages reviewers to visit the website frequently and contribute to the review community.

Drawing upon the findings in the literature, we argue that reviewers' reputation and online users' attention would be viewed as important social rewards to the reviewers. In other words, reviewers would write reviews to attract the attention of other users and gain reputation so as to reward their efforts.

While we are aware of the impact of online reviews and the motivations for online reviewers to provide these reviews, little has been studied as to how social incentives and motivations affect reviewers' actions and decisions. In other words, there is a gap in the literature linking the underlying motivations for reviewers to contribute and the outcome of their contributions, i.e. the online reviews they provide. In this study, we try to fill in this gap by studying how social incentives drive reviewers' contributions and how online reviewers compete for attention.

A FRAMEWORK FOR ONLINE REVIEWER'S DECISION MAKING PROCESS

In this section, we first present the underlying rationale for reviewers to strategically compete for attention in online review communities. Then we develop a theoretical framework to model the online reviewers' decision making process and present our hypotheses for testing the framework.

We build our arguments upon Hansen and Haas (2001), who study electronic document suppliers' strategies to compete for attention in an internal knowledge market. An internal knowledge market is defined as electronic document dissemination in an organization (Hansen and Haas 2001). This market has a set of electronic document suppliers and users, rewards for supplying and using the electronic documents, and a poses a problem for users to easily identify appropriate documents due to ambiguous quality and large quantities of documents. The scenario studied in Hansen and Haas (2001) is very similar to that in online review context as discussed below.

Online Review System

The online review system shares four characteristics with the internal knowledge market in an organization as described in Hansen and Haas (2001). First, there is a distinct set of online consumers who search online reviews when making a purchase decision. These consumers will use the information in online reviews to help them to make purchase decisions. Second, there is a distinct set of suppliers, in this setting online reviewers, who offer personal evaluations of products. These reviewers post online reviews to help potential buyers make a purchase decision.

Third, both online reviewers and consumers will receive benefits by posting reviews or by reading reviews, which create incentives for reviewers and consumers to offer reviews and to search for reviews. For reviewers, they receive social rewards in terms of obtaining attention and improving their reviewer rank. For consumers, they benefit from using the product information in reviews to improve their purchase decisions (Li and Hitt 2008).

Finally, consumers are likely to experience the problem of finding the most useful reviews when searching product information. Since reviews are experience goods in nature whose quality may not be fully assessed before reading them (Nelson 1970), consumers may have difficulty finding the most appropriate review to read (Chen et al. 2006). One way to mitigate this problem is to provide perfect assessment as to the quality of each review. However, without such perfect assessment, it is hard for consumers to identify the right reviews. Therefore, this creates a processing problem for consumers when trying to identify the right review (Chen et al. 2006, Forman et al. 2008).

Reviewers' Strategies to Gain Attention

The problem for consumers of finding the most useful reviews can be solved if consumers can allocate sufficient amount of time and effort to read through all the reviews. However, given the limited attention each consumer is able to spend, it is unlikely that a consumer will process all the available reviews before purchase (Chen et al. 2006, Forman et al. 2008). Consumers have to use heuristics to select a subset of the reviews to read rather than processing all the reviews systematically (Forman et al. 2008). This constraint on consumers' limited attention has implications for reviewers' decisions on creating and posting reviews. Reviewers have to adopt the right strategy so as to compete for the scarce attention from consumers. Next, we develop a two-step framework for modeling the reviewer's decision making process and state the hypotheses used to test our framework.

Product Choice: Popularity vs. Crowdedness

In order to effectively compete for attention, reviewers have to choose an appropriate product for which to post a review. This involves balancing the *popularity* of the product and the *crowdedness* of the review segment for that product. The *popularity* of a product is determined by the sales volume of the product. Since sales volume indicates the product awareness in the market (Godes and Mayzlin 2004, Liu 2006), it provides a good measurement of the amount of potential consumers who may pay attention to the reviews. Therefore, popularity indicates the total attention a product may attract. The *crowdedness* of a review segment is determined by the number of existing reviews for the product. This measures the level of competition for attention in the review segment of that product.

The popularity of a product will have a positive effect on reviewers' choices. It indicates the number of existing adopters of the product which signals the social pressure for potential buyers (Bass 1969). These potential buyers will seek review information in order to make a purchase decision. A higher level of popularity implies a higher level of market awareness of the product (Godes and Mayzlin 2004) and therefore this product would have more future buyers who pay attention to the reviews. This effect provides incentives for potential reviewers to review a popular product since the level of total attention for a popular product is usually higher than that for an obscure product. By reviewing a popular product, the reviewer is able to share from a larger pie of total attention than when reviewing an obscure product. Therefore we hypothesize:

H1: As the level of the popularity of a product increases, more reviewers will review the product.

While the popularity could positively affect the total attention that a review can share from, the crowdedness of a review segment would have a negative effect on the amount of attention each individual review can gain (Hansen and Haas 2001). The crowdedness of a review segment directly measures the level of competition for attention. In other words, the more crowded a review segment is, the more competition for attention one individual review faces. Since there are more reviews competing for attention within a crowded review segment, it is not easy for one individual review to outperform other reviews in order to gain attention. One can easily drown in the flood of numerous reviews. In contrast, if a reviewer chooses to post a review in a less crowded review segment, they may easily become a big fish in a small pond. Therefore, with the increasing level of the crowdedness of the review segment, fewer reviewers would choose to provide reviews for that product.

H2: As the level of the crowdedness of a product's review segment increases, fewer reviewers will review the product.

Content Choice: Imitation vs. Differentiation

After choosing a product, reviewers have to choose a strategy in order to compete against other reviews. They can choose a safe strategy by following previous mass opinions, i.e. the *imitation* strategy, or a risky strategy by offering a differentiated opinion, i.e. the *differentiation* strategy. Offering a differentiated opinion to deviate from the rest of the reviews could be an effective way to capture attention. Prior studies suggest that using distinctive web content such as color or animation can attract more attention (e.g. Benbasat and Dexter 1986, Hong et al. 2004, Zhang 2000). Similarly, posting a distinctive review rating could help reviewers attract more attention from potential buyers simply due to the visual distinctiveness effect (Smith and Goodwin 1971).

However, deviating from the consensus of other reviews may bring negative feedback. Online reviews are different from other web content such as online ads or news. Reviews reflect personal opinions of community members and offer advice to other community members. Postmes et al. (2000) point out that online community members desire behaviors that are consistent with the community norms. Thus, reviews that are patterned after community norms are easy to communicate to others and can help establish reviewers' reputations (Forman et al. 2008, Resnick et al. 2000). In other words, reviews with similar suggestions as the majority of current existing reviews would deliver a positive impression to potential buyers and are easy to communicate. Therefore, using a differentiation strategy could be risky as these differentiated reviews are inconsistent with the community consensus. Community members would treat inconsistent information negatively.

As a result, using a differentiation strategy may help to increase short term attention but could hurt the long term reputation of a reviewer by receiving negative feedback. Adopting an imitation strategy may not be as attractive as the differentiation strategy to reviewers at first glance. It may turn out to be rewarding in terms of enhancing reviewers' long term reputations. Whether to choose an imitation strategy or a differentiation strategy would depend on balancing between the benefit from gaining attention and the cost of hurting reputation. For reviewers with an established reputation, it may not be a wise choice to take the risk of differentiating from the mass opinion since the cost of hurting their reputation would be relatively high. However, for novices or reviewers with low reputation costs, adopting a differentiation strategy could be an attractive option since they might benefit more from the gain of attention than the loss of reputation.

H3a: Reviewers with high reputation costs are more likely to adopt the safe strategy by imitating existing ratings at the current time period.

H3b: Reviewers with low reputation costs are more likely to adopt the risky strategy by differentiating from existing ratings at the current time period.

Figure 1 presents the proposed framework of the reviewer's decision making process. Reviewers will have to make strategic decisions in two steps in order to compete for attention as a reward for their voluntary contributions. In the next section, we present our empirical methods.

[Insert Figure 1 here.]

EMPIRICAL METHODOLOGY

Data

This study uses book reviews on Amazon.com to test the hypotheses. We selected Amazon as it is the largest online book retailer which sells about 44% of the entire bookstore sales in 2010 (Rosenthal 2011). It has also been used to study research questions regarding online reviews by various previous studies (e.g. Chen et al. 2006, Forman et al. 2008, Li and Hitt 2008, Mudambi and Schuff 2010). Our sample includes all books released in September and October 2010 which contains 1,751 books. At the end of data collection period, there are 690 books which have more than 2 reviews and 8,125 reviews in the data set.

The data in our sample includes daily information on books, reviews, and reviewers. For books, we collect the book's release date and its daily sales rank which will be used as a proxy of its popularity. For reviews, we collect the date when the review is posted, the reviewer's user name which could be a real name or a pen name, the review rating, and the total vote (this is used as a proxy of the amount of attention a review has captured). The votes are collected daily. We then obtain the reviewer rank from each reviewer's online profile on Amazon (Amazon ranks reviewers based on the number of reviews and the quality of their reviews[1]). One unique feature of our sample is that we collect all the information from the release date of the books. Therefore, we are able to observe the dynamics of reviewers' strategies over the time period of the sample. The data spans a three-month period from September 2010 to November 2010.

In addition, for the same book list and during the same data collection period, we collected a similar data set from BarnesandNoble.com. This data set is used for cross site analysis to

[1] Amazon uses the ratio of (Helpful vote)/(Total vote) to measure the quality of a review. In addition, they claim that they consider the relative magnitude of the amount of the total vote at the same time.

verify that reviewers' behaviors on Amazon are greatly motivated by social incentives. We report the results in the robustness check section.

Lastly, we randomly selected about 500 electronic products on Amazon which include laptops, netbooks, tablets, blu-ray players, GPSs, TVs, and digital cameras. This data set is used for cross category comparison in order to generalize our results from books to other product categories. The data collected in the electronic product dataset is similar to that of the book dataset. The results are reported in the robustness check section.

Empirical Model

Product Choice

Our purpose is to study how two factors, popularity and crowdedness, can affect reviewers' decisions on choosing a product to review. The data is unbalanced panel data for a three-month period and is grouped at the book level. We construct a dependent variable *DailyReviewNumber* which is the count of the daily number of new reviews for each book. This variable directly measures how many reviewers choose to review a book each day knowing the popularity and the crowdedness of that book on that day. By understanding how these two factors can affect the arrival process of reviews, we can infer how reviewers make decisions based on these two factors.

Since our dependent variable is a count variable, we cannot use the traditional Ordinary Least Square (OLS) model as the assumptions of homoscedasticity and normal distribution of the errors are violated. A common model to account for the discrete and non-negative nature of the count data is the Poisson model which has been widely used in the marketing literature to study consumers' purchasing behaviors (e.g. Gupta 1988, Dillon and Gupta 1996, Schmittlein et al.

1987, Wagner and Taudes 1986). We assume the arrival of reviews (i.e. the *DailyReviewNumber*) follows a Poisson distribution. Note that the Poisson model assumes equal mean and variance. Since we find over-dispersion in our data, we estimate a negative binomial distribution model which allows for over-dispersion of the count variable (Hausman et al .1984).

The process of a book receiving reviews can be captured by a Poisson process. Therefore, the probability that a book *i* obtains reviews at time *t* with review arrival rate $\boldsymbol{\lambda_{it}}$ can be presented as:

$$\boldsymbol{P_{it}}(\boldsymbol{Y_{it}} = \boldsymbol{y} | \boldsymbol{\lambda_{it}}) = \frac{\boldsymbol{e^{-\lambda_{it}} \lambda_{it}^{y}}}{\boldsymbol{y}!}, y = 0, 1, 2, \ldots \quad (1)$$

where $\boldsymbol{Y_{it}}$ is the *DailyReviewNumber* of book *i* at time *t*. To account for the popularity and crowdedness effects, we model the review arrival rate following Dillon and Gupta (1996) and Gupta (1988).

$$\boldsymbol{\lambda_{it}} = exp\,(\boldsymbol{\gamma_i} + \boldsymbol{a'Z_{it}} + \boldsymbol{\varepsilon_{it}}) \quad (2)$$

where $\boldsymbol{Z_{it}}$ is the vector of the explanatory variables and $\boldsymbol{a}$ is the vector of parameters. γ_i is the book-specific fixed effects which controls for the intrinsic value of book *i*. $\boldsymbol{\varepsilon_{it}}$ is the error term. We performed the Hausman (1978) test to test the validation of using a fixed effects model or a random effects model. The Hausman test checks whether the assumption that the random effects specification is uncorrelated with the independent variables is violated. Our result rejects the null hypothesis at the 1% significance level and is in favor of using a fixed effects model. Using fixed effects model allows the error term to be correlated with the explanatory variables which makes the estimation more robust. Moreover, it controls for the time-invariant unobserved characteristics such as quality of books or author name effects that are associated with each book which may affect the arrival rate of the reviews.

The independent variables include the natural log of book *i*'s sales rank at the previous day *t-1* ($SalesRank_{it-1}$) and the natural log of the number of existing reviews at the previous day *t-1* ($ReviewNumber_{it-1}$). *SalesRank* measures the popularity of the book and *ReviewNumber* measures the crowdedness of the review segment for that book. We use the previous day *SalesRank* and *ReviewNumber* to directly estimate the impact of existing popularity and crowdedness on reviewers' product choice decisions in the current period. Since *SalesRank* is negatively correlated with the popularity of a product, we expect the coefficient to be negative. As predicted by H1, reviewers are more likely to review popular products than obscure or niche products. H2 predicts the coefficient for *ReviewNumber* to be negative since reviewers would try to avoid the intense competition for attention in a crowded review segment.

Our model is different from the models used in the online review literature that try to assess the impact of online reviews on product sales. First, the dependent variable in our model is the daily count of new reviews rather than the cumulative number of reviews. This variable does not have the cumulative effect of reviews that could potentially drive product sales. Second, we use the previous period sales rank rather than the current or the following period sales rank. Even if the daily count of reviews might potentially affect sales, it would not be able to affect the previous period's sales. Therefore, our model does not contradict to the previous findings that the cumulative number of reviews can drive product sales. In addition, we calculate the variance inflation factor (VIF) value for every variable in all models to check for potential multicollinearity. All the VIF values are below 10 which suggest no serious multicollinearity in our results (Hair et al. 1995, Marquardt 1970, Mason et al. 1989).

One may still argue that the number of daily reviews could be affected by the cumulative sales volume. That is, the number of potential reviewers is proportional to the existing adopters who have already purchased the product. High cumulative sales volume indicates more potential reviewers and could lead to more future daily reviews. To control for this effect, we construct a variable *PotentialReviewers* to account for the possibility that the increasing number of daily reviews is simply due to the increasing number of potential reviewers over time. Since the *SalesRank* is a good proxy for the sales volume, the cumulative *SalesRank* can be used as a reasonable proxy for the existing adopters which indicates the number of potential reviewers. However, the sales rank is negatively correlated with the sales volume, i.e. the smaller the sales rank, the higher the sales volume is. We use the inverse of the *SalesRank* to account for this effect. $PotentialReviewers_{i,t-1}$ is defined as the sum of the inverse of *SalesRank* from book i's release date to the previous day $t-1$:

$$PotentialReviewers_{i,t-1} = \sum_{\tau=t_0}^{t-1} \frac{1}{SalesRank_{i\tau}} \tag{3}$$

where t_0 = the release date of book i, and t = the current date. We use $PotentialReviewers_{it-1}$ to control for the size effect of potential reviewers on the daily number of reviews.

Lastly, reviewers may lose interest in writing reviews for products that have been released for some time. Their enthusiasm for writing reviews may decay over time, which can affect the number of daily reviews at different time periods. We construct a variable $DaysElapsed_{it}$ to control for the time effect. $DaysElapsed_{it}$ is the number of days since book i's release date.

Figure 2 summarizes the relationships between the variables and the expected impact in the model used to test H1 and H2.

[Insert Figure 2 here.]

Content Choice

The purpose of studying reviewer's content choice is to examine how reviewers choose a rating strategy to balance between gaining attention and hurting reputation (i.e. receiving negative feedback). Before we test our H3, we need to first establish the trade-off for reviewers in choosing between the two strategies. The trade-off includes two parts, which are the benefit and the cost that a risky strategy brings. First, we examine whether a differentiated rating can attract more attention to confirm that reviewers can benefit from taking the risky strategy. Then, we test whether a differentiated rating brings more negative feedback to show the cost of taking the risky strategy.

The data is unbalanced panel data that is grouped at the review level. We use daily total votes ($DailyTotalVote_{ijt}$) and daily unhelpful votes ($DailyUnhelpfulVote_{ijt}$) as two dependent variables to measure the level of attention and negative feedback for each review on each day. These two variables are count variables. Therefore, as discussed above, we assume the daily total votes and daily unhelpful votes follow a Poisson distribution. Due to over-dispersion in our data, we use the negative binomial distribution model to test the benefit and the cost effects.

The probability of review *j* of book *i* obtaining votes at time *t* with vote arrival rate $\boldsymbol{u_{ijt}}$ can be presented as:

$$P_{ijt}(\boldsymbol{X_{ijt}} = x|\boldsymbol{u_{ijt}}) = \frac{e^{-u_{ijt}}u_{ijt}^{x}}{x!},\ x = 0,\ 1,\ 2,\ \ldots \qquad (4)$$

where $\boldsymbol{X_{ijt}}$ is the number of daily votes for review *j* of book *i* at time *t*. To account for the effects from reviewers' rating strategies, the vote arrival rate $\boldsymbol{u_{ijt}}$ can be expressed as a function of the explanatory variables, $\boldsymbol{R_{ijt}}$, which include both independent variable and control variables. $\boldsymbol{b}$ is the vector of the coefficients. $\boldsymbol{\theta_{ij}}$ is the review-specific fixed effects and $\boldsymbol{\varepsilon_{ijt}}$ is the error term. We performed the Hausman (1978) test to check whether a fixed effects model or a random effects model should be used. The result rejects the null hypothesis at the 1% significance level and is in favor of using the fixed effects model.

$$\boldsymbol{u_{ijt}} = exp\,(\boldsymbol{\theta_{ij}} + \boldsymbol{b}'\boldsymbol{R_{ijt}} + \boldsymbol{\varepsilon_{ijt}}) \tag{5}$$

The independent variable of interest is $RatingDeviation_{ijt}$, which is the squared difference between the average rating for book *i* at time *t-1* and reviewer *j*'s rating, i.e. $RatingDeviation_{ijt} = (AvgRating_{it-1} - Rating_{ij})^2$. This variable measures the distance from the focal rating to the average rating. Therefore, it indicates whether the reviewer is using a differentiation strategy or an imitation strategy. A large value of *RatingDeviation* implies that the reviewer is trying to differentiate from others while a value close to zero indicates that the reviewer is following the mass opinion. A positive coefficient of *RatingDeviation* for both models shows that using the differentiation strategy would bring more attention (i.e. more total votes) and more negative feedback (i.e. more unhelpful votes) at the same time.

The control variables include the characteristics of the book and the reviewer which could affect the level of attention and negative feedback of a review. For the characteristics of books, we control for the popularity of the book at the previous period ($SalesRank_{it-1}$), and the crowdedness of the review segment ($ReviewNumber_{it-1}$). The more popular the book is, the more likely the review will get a vote. However, the more crowded the review segment is, the less likely the review will get a vote.

For the characteristics of reviewers, we control for reviewers' reputation in the previous period ($ReviewerRank_{ijt-1}$), and the identity disclosure status ($Realname_{ij}$). The $ReviewerRank_{jt}$ is the natural log of the reviewer's rank for review *j* for book *i* at time *t*. The *Realname* variable is a dummy variable which is 1 if the reviewer discloses his or her real world name and 0 otherwise.

In addition, we use $DaysElapsed_{ijt}$ to control for the time decay effect on the daily number of votes. We control for the previous total level of attention $TotalVote_{ij,t-1}$ when estimating the benefit from the differentiation strategy, and the previous total negative feedback, $TotalUnhelpfulVote_{ij,t-1}$, when estimating the cost. These two variables control for the possible herding effect where online users' attention or opinions may simply follow those of previous users'.

After understanding the impact of different strategies on the flow of attention, we then examine reviewers' decisions on choosing an appropriate strategy. As predicted in H3a and H3b, reviewers with high reputation costs would tend to use the safe strategy by following mass opinion, while reviewers with low reputation costs would be more likely to differentiate from others. We use $RatingDeviation_{ij}$ as the dependent variable to investigate reviewers' rating choices. We estimate the following model by using data on the day before the review is posted. Using data on the previous day allows us to replicate the environment when reviewers make the rating decisions.

$$\begin{aligned} RatingDeviation_{ij} = {} & \beta_0 + \beta_1 ReviewerRank_{ij} + \beta_2 RealName_{ij} + \beta_3 SalesRank_i \\ & + \beta_4 ReviewNumber_i + \varepsilon_{ij} \end{aligned} \tag{6}$$

A positive coefficient of *ReviewerRank*, β_1, indicates that top ranking reviewers are posting less differentiated ratings than low ranking reviewers.

RESULTS

We estimate our empirical models using unbalanced panel data over a period of three months. The negative binomial distribution models are estimated via the maximum likelihood method. Table 1 shows descriptions of all the variables and Table 2 summarizes the descriptive statistics for the variables. Note that *Rating* and *RealName* are time invariant variables. All the other variables change every day.

[Insert Table 1 and Table 2 here.]

Table 3 presents the fixed effects panel data estimation results for the model of choosing a book to review. Both coefficients of interest have the negative sign and are significant at the 1% significance level for models in column (1), (2) and (3). As predicted by H1, the more popular the book, the more potential buyers are aware of the product. Therefore, an individual review is able to share from more total attention. As a result, more reviewers will choose to review the book, i.e. the coefficient for *SalesRank* is negative. Note that after controlling for the effect from the number of potential reviewers, we still observe a significant effect for *popularity*.

[Insert Table 3 here.]

For H2, the higher the number of coexisting reviews indicating a higher level of *crowdedness*, the more severe the competition for attention. Consequently, we find that fewer reviewers will choose to review a book as the review segment becomes crowded, i.e. the coefficient of *ReviewNumber* is negative and significant at the 1% level. This indicates that reviewers tend to avoid crowded review segments so as to reduce the competition for attention. Note that after controlling for the time decay effect, we still observe a significant negative impact from crowdedness on a reviewer's book choice. Therefore, we find support for both H1 and H2.

Interestingly, these results are consistent with the strategies proposed by Peter Durward Harris, a top 10 Amazon reviewer. In an article he shared on Amazon, he suggested that based on his experience, the ideal products to review were "products that attracted a reasonable amount of traffic but not many reviews" (Harris 2009, p. 1). Our results indicate that reviewers seem to follow these rational rules in order to strategically gain attention and avoid competition.

Next, we analyze reviewers' decisions on choosing an appropriate rating strategy. To analyze their rating strategies, we need to first establish the cost and benefit in choosing between the imitation and the differentiation strategy. Table 4 reports the fixed effects panel data estimation results for the benefit and cost of using the differentiation strategy. The column "Gaining Attention" shows the benefit from being differentiated and the model uses *DailyTotalVote* as the dependent variable. The column "Receiving Negative Feedback" shows the cost of deviating from the consensus and the model uses *DailyUnhelpfulVote* as the dependent variable.

[Insert Table 4 here.]

The variable of interest is *RatingDeviation* which indicates the strategy used by reviewers. A large value of *RatingDeviation* implies a differentiation strategy and a small value implies an imitation strategy. We find the coefficient of *RatingDeviation* is positive and significant at the 1% significance level for both models. This suggests that the more differentiated the rating, the more attention a review can gain but the more unhelpful votes it receives at the same time. Therefore, reviewers will face a trade-off when deviating from the mass opinion. They have to balance between the cost and the benefit when making their decision. In other words, reviewers with different reputation costs would have to adopt different strategies so as to obtain more net benefits. In addition, the negative sign of the coefficients of *SalesRank* and *ReviewNumber* helps to explain our previous findings on reviewer's book choices. The more popular the book, the more votes a review receives. The more crowded the review segment, the fewer votes a review receives.

After we establish the cost and benefit for using the risky strategy, we are able to analyze reviewers' strategic behaviors when posting ratings. The dataset includes only the data on the day a review is posted. This allows us to reproduce the environment when reviewers make decisions and examine how they choose a strategy given the information at that time. Table 5 presents the OLS regression results for testing H3a and H3b. The coefficient for *ReviewerRank* is positive and significant. This implies that for top ranking reviewers whose reputation costs are relatively high, they will be more likely to adopt a safe strategy by offering a less differentiated rating. However, for low ranking reviewers, since their reputation costs are relatively low, they tend to offer more differentiated ratings. In other word, the benefits from gaining attention for low ranking reviewers would outweigh their costs of losing reputation. Therefore, we find support for H3a and H3b.

[Insert Table 5 here.]

Table 6 summarizes the results from the above analysis. We find support for all of our hypotheses. Our results indicate that online reviewers do not randomly select books to review but tend choose a popular but less crowded book to review. Moreover, reviewers rate the book by considering the cost and benefit they can gain from the review. That is, the benefit from gaining attention and the cost of hurting reputation. Interestingly, high reputation reviewers tend to be more conservative by adopting a safe strategy more frequently than low reputation reviewers.

[Insert Table 6 here.]

ROBUSTNESS CHECK

To strengthen our findings and rule out alternative hypotheses, we conducted several robustness checks of our analysis. First, to further understand reviewer's book choices, we compare two different review systems, Amazon and BN. Second, we analyze another product category, electronic products, to eliminate possible sample selection bias with books. Third, we include the text of the review in addition to numerical ratings in analyzing reviewer's rating strategies. Finally, we test alternative models to accommodate the possible correlation between reviewer rank and votes. With these additional analyses, we show that our previous results hold true and thus are robust.

Different Review Systems: Amazon vs. BN

Amazon and BN are the top two online book retailers. The review systems on these two sites are similar but with one critical difference. Reviewers are not ranked on BN but are on Amazon. Without a reviewer ranking system, reviewers on BN would be less likely motivated by competition among peers than those on Amazon. Therefore, the difference in reviewers' behaviors observed between the two sites can be attributed to the different design of the review systems, i.e. the lacking of a ranking system which induces competition among reviewers.

We collected a similar dataset on BN using the same book list and during the same time period as the data we collected on Amazon. At the end of data collection period, there are 460 books which have more than 2 reviews on BN. Since in general there are fewer reviews on BN than on Amazon and the sales rank of these two sites is on a different scale, we normalize the variables so that the results are comparable (see the footnote in Table 7). Table 7 reports the estimated results using data from both sites. *Amazon* is a dummy variable which is 1 if the data is from Amazon and 0 if it is from BN. *AmazonReviewNumber, AmazonSalesRank, AmazonPotentialReviewers,* and *AmazonDaysElapsed* are interaction terms which measure the difference of main effects between the two sites.

[Insert Table 7 here.]

Interestingly, we find that while popularity has a positive effect on both sites, crowdedness has different effects on different sites. The negative coefficient of *ReviewNumber* on Amazon indicates that reviewers are worried about the competition among reviewers—they are less likely to post reviews for books which have more existing reviews. In contrast, the positive coefficient of *ReviewNumber* on BN indicates that reviewers are more likely to post reviews for books which have more existing reviews. It suggests that reviewers on BN do not consider the potential competition; instead, they follow the "buzz" when selecting a certain book to review. The difference in reviewers' behaviors could be attributed to the difference in design of these two sites. The reviewer ranking system on Amazon may not only increase reviewers' motivation to write reviews, but also stimulate competition among reviewers. The introduction of different review system mechanisms may force reviewers to adopt different strategies on different review websites.

Different Product Categories: Books vs. Electronics

In our main analysis, we use data from the book category to test all of our hypotheses since Amazon is the market leader in the retail book industry. One may argue that there could be a potential sample selection bias such that reviewers may behave differently when reviewing different types of products. To eliminate the bias from using only books, we collected reviews from the electronic products category on Amazon during the same data collection period. We run the same fixed effects analysis using the electronic products dataset and the results are shown in Table 8.

[Insert Table 8 here.]

The results from the electronic products category are consistent with our previous results from books. The negative coefficients of *SalesRank* and *ReviewNumber* confirm our previous findings in the book category. Reviewers' strategic decisions on choosing products to review do not exhibit significant differences between product categories. When reviewing electronic products, reviewers still consider both popularity and crowdedness effects when selecting a product to review. Thus, our previous results are robust.

Review Content: Rating vs. Text

Although most of the existing studies on online reviews focused on review ratings rather than review text, the sentiment of review text may also play a role in reviewers' review decisions in addition to the numerical ratings. To measure the sentiment of review text, we use the negative word list in the Harvard Psychosociological Dictionary, specifically Harvard IV-4 dictionary. The Harvard's General Inquirer (details available at http://www.wjh.harvard.edu/~inquirer/) classifies words into 182 categories such as positive, negative, strong, weak, etc. The negative word category has been commonly used in the finance and accounting literature to examine the tone and sentiment of corporate 10-K reports (e.g. Loughran and McDonald 2011) or *Wall Street Journal* news stories (e.g. Tetlock 2007, Tetlock et al. 2008).

Following prior research, we use the frequency of negative words to measure the sentiment of review text. $PerNegWords_{ij}$ is defined as the percentage of the number of negative words in review j of book i. $AvgPerNegWords_{it}$ is the mean of *PerNegWords* across all existing reviews of book i at time t. To understand reviewers' strategies on text tone, we construct a variable, *NegTextDeviation*, which is similar to *RatingDeviation* in the above analysis. $NegTextDeviation_{ijt}$ is defined as $NegTextDeviation_{ijt} = (AvgPerNegWords_{it-1} - PerNegWords_{ij})^2$. Next, we replace the dependent variable in equation (6) with $NegTextDeviation_{ij}$ and control for the total number of words in each review. $Length_{ij}$ is the natural log of the total number of words in review j of book i. Since equation (6) and (7) are interlinked and the errors terms are correlated, we estimate the two models simultaneously through seemingly unrelated regression (SUR).

$$NegTextDeviation_{ij} = \beta_0 + \beta_1 ReviewerRank_{ij} + \beta_2 RealName_{ij} + \beta_3 SalesRank_i + \beta_4 ReviewNumber_i + \beta_5 Length_{ij} + \varepsilon_{ij} \qquad (7)$$

Table 9 reports the estimation results from SUR. The positive coefficient of *ReviewerRank* in both models indicates that high ranking reviewers post less deviated reviews in terms of the ratings and in terms of the percentage of negative words. In contrast, low ranking reviewers tend to offer more differentiated and more deviated reviews in terms of the ratings and in terms of the percentage of negative words. Moreover, the negative coefficient of *Length* suggests that long reviews are more likely to be less deviated in terms of the percentage of negative words.

[Insert Table 9 here.]

Alternative Measure of Cost to Reviewers

To check the robustness of our measurement of reviewers' cost *ReviewerRank*, we generate a new variable, *ReviewerExperience*, as an alternative measurement to replace *ReviewerRank*. $ReviewerExperience_{ijt}$ is the natural log of the total number of reviews that a reviewer has posted by time *t*. It is independent from the other variables in the model and is highly correlated with reviewer rank. A higher value of *ReviewerExperience* means the more number of reviews a reviewer has posted, and thus the more time and effort that reviewer has devoted to the review system. As a result, the reviewer would care more about the outcome of his or her reviews and suffer more costs when receiving negative votes. We estimate the model with the original dataset but replace *ReviewerRank* with *ReviewerExperience*. The results are reported in Table 10. The key variable *RatingDeviation* is still positive and significant.

[Insert Table 10 here.]

Similarly, we replace *ReviewerRank* with *ReviewerExperience* in the model for testing H3a and H3b to check the robustness of the results. Table 11 summarizes the results when *ReviewerExperience* is used. The negative coefficient of *ReviewerExperience* confirms our previous findings that reviewers with more experience (most likely high ranking reviewers) tend to deviate less from the average than reviewers with less experience (most likely low ranking reviewers).

[Insert Table 11 here.]

DISCUSSION AND CONCLUSION

This paper studies how online reviewers compete for attention by choosing different strategies under different conditions. To the best of our knowledge, this is the first attempt to theorize and empirically test how online information suppliers' behaviors are driven by the desire for gaining attention and online reputation. Theoretically, it fills in the gap in the literature on how social motivations can affect information suppliers' behaviors. The majority of prior literature is focused on understanding the consequences of web content or online information, such as the impact of online reviews on product sales. Different from these previous studies, we try to investigate the antecedent of web content. That is, online reviewers' strategic behaviors under the social incentives of gaining peers' attention and enhancing their online reputation. Interestingly, we find that product popularity and review segment crowdedness have two opposite effects on reviewers' review decisions. Moreover, reviewers with high reputations tend to offer more modest ratings and use fewer negative words than unknown reviewers. Our comparison of two different review systems confirms that these strategic behaviors are likely the result of the introduction of social incentives which stimulate competition for attention among reviewers. Since attention is usually virtual in nature and difficult to quantify, this paper offers a unique way to empirically measure attention and to study how online users compete for attention.

This study yields several interesting managerial implications. First, our findings indicate that reviewers are more likely to write a review for popular but uncrowded products, which can be beneficial to designers of websites which feature reviews. We suggest that a website may consider emphasizing these two dimensions differently on the product review page. For example, for popular and crowded products, the website may emphasize the popularity of the product but not on the large number of existing reviews. However, for niche products with few existing reviews, the website may highlight the small number of existing reviews to entice more reviews, but avoid displaying the unpopular nature of the product.

Second, the comparison between Amazon and BN shows that the mechanism of an online review system has a significant impact on reviewers' behaviors. Offering social incentives such as providing reviewer ranks to quantify reviewers' online reputations can induce competition among reviewers. Reviewers may become strategic players in such an environment. Companies can utilize reviewers' rationale reactions towards social incentives to adjust the flow of reviews to some extent. For example, to avoid competition for attention, reviewers are less likely to review a product when its review segment becomes crowded. It provides great opportunities for companies to increase the review volume for niche products. Companies may send invitation emails to niche product buyers and emphasize the small number of existing reviews, or increase the social incentives for reviewing niche products such as adding more weight to reviews of niche products when calculating reviewer rank.

Third, our results on reviewers' rating and text strategies suggest that reviewers with different levels of online reputation tend to provide different ratings and use different tones in their review text. Depending on specific goals, companies may develop different algorithms for selecting certain groups of reviewers to whom to send review invitations rather than sending invitations to every buyer, currently the most common practice. For example, if the company desires to have large variation in reviews, it can send more invitations to low ranking reviewers than high ranking reviewers. In contrast, if the company prefers low variation and consistent reviews, it should avoid sending too many review invitations to unknown reviewers and should invite more high ranking reviewers to contribute.

Finally, companies may signal consumers of those reviewers offering consistently highly differentiated reviews to help facilitate consumers' decisions on the most useful reviews to read. Companies may symbolize these reviewers by flagging the reviewer or labeling the reviewer so that consumers can easily identify those outlying reviewers in addition to using reviewer rank as an identifier.

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Table 1. Description of Variables

Variable	Description
Variables regarding books	
$DailyReviewNumber_{it}$	The number of reviews that book *i* receives at day *t*
$ReviewNumber_{it}$	The natural log of the cumulative number of reviews of book *i* from its release date to day *t*
$SalesRank_{it}$	The natural log of the sales rank of book *i* at day *t*
$PotentialReviewers_{it}$	The sum of the inverse of *SalesRank* from book *i*'s release date to day *t*
$DaysElapsed_{it}$	The number of days from book *i*'s release date to day *t*
Variables regarding reviews	
$RatingDeviation_{ijt}$	The square of the difference between the rating of review *j* of book *i* and the average rating at day *t*
$Rating_{ij}^{\dagger}$	The rating of review *j* of book *i* (one-to-five scale)
$DailyTotalVote_{ijt}$	The number of votes that review *j* of book *i* receives at day *t*
$DailyUnhelpfulVote_{ijt}$	The number of unhelpful votes that review *j* of book *i* receives at day *t*
$TotalVote_{ijt}$	The cumulative number of votes that review *j* of book *i* receives from the day it posted to day *t*
$TotalUnhelpfulVote_{ijt}$	The cumulative number of unhelpful votes that review *j* of book *i* receives from the day it posted to day *t*
$DaysElapsed_{ijt}$	The number of days from the posting date of review *j* of book *i* to day *t*
Variables regarding reviewers of reviews	
$ReviewerRank_{jt}$	The natural log of the reviewer's reviewer rank of review *j* of book *i* at day *t*
$Realname_{j}^{\dagger}$	A dummy variable measuring the real name identity of the reviewer of review *j* of book *i* 1 = the reviewer uses a real name, 0 = the reviewer uses a pen name.

† Variables are time invariant.

Table 2. Descriptive Statistics of Variables					
Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
DailyReviewNumber	83,644	.178	1.293	0	231
ReviewNumber	83,644	1.419	1.125	0	6.059
SalesRank	83,644	9.557	2.384	.693	15.438
PotentialReviewers	83,644	3.656	2.761	.066	38.934
RatingDeviation	574,150	1.004	1.819	0	15.793
Rating	574,150	4.159	1.184	1	5
DailyTotalVote	574,150	.084	.694	0	248
DailyUnhelpfulVote	574,150	.031	.500	0	236
TotalVote	574,150	6.293	20.364	0	925
TotalUnhelpfulVote	574,150	2.201	12.178	0	885
ReviewerRank	574,150	9.843	4.059	1.386	15.825
Realname	574,150	.520	.499	0	1

Table 3. Fixed Effects Estimation on Book Choice ($DailyReviewNumber_{it}$)			
Variable	**(1)**	**(2)**	**(3)**
$SalesRank_{i,t-1}$	-.195**		-.205**
	(.009)		(.009)
$ReviewNumber_{i,t-1}$		-.129**	-.181**
		(.020)	(.020)
$PotentialReviewers_{it-1}$	.033**	.084**	.051**
	(.006)	(.006)	(.006)
$DaysElapsed_{it}$	-.016**	-.025**	-.013**
	(.001)	(.001)	(.001)
N	40,568	40,568	40,568
Log Likelihood	-21640.015	-21824.988	-21600.537

Note: ** $p < 0.01$, * $p < 0.05$

Table 4. Fixed Effects Estimation for Cost and Benefit from Differentiation Strategy

Variable	Gaining Attention: $DailyTotalVote_{ijt}$ (Benefit)	Receiving Negative Feedback: $DailyUnhelpfulVote_{ijt}$ (Cost)
$RatingDeviation_{ijt-1}$	$.093^{**}$	$.114^{**}$
	(.006)	(.009)
$SalesRank_{it-1}$	$-.245^{**}$	$-.351^{**}$
	(.006)	(.011)
$ReviewNumber_{it-1}$	$-.853^{**}$	-1.103^{**}
	(.013)	(.022)
$ReviewerRank_{ijt-1}$	$-.037^{**}$	$-.035^{**}$
	(.002)	(.003)
$RealName_{ij}$	$-.194^{**}$	$.326^{**}$
	(.044)	(.084)
$DaysElapsed_{ijt}$	$-.014^{**}$	$-.011^{**}$
	(.0004)	(.001)
$TotalVote_{ij,t-1}$	$-.002^{**}$	
	(.0002)	
$TotalUnhelpfulVote_{ij,t-1}$		$-.002^{**}$
		(.0003)
N	344,205	228,298
Log Likelihood	-76281.890	-30459.596

Note: ** $p < 0.01$, * $p < 0.05$

Table 5. OLS Estimation on Choosing Rating Strategies

$ReviewerRank_{ij}$	$.010^{**}$
	(.004)
$RealName_{ij}$	$-.120^{**}$
	(.046)
$ReviewNumber_{i}$	$-.054^{**}$
	(.008)
$SalesRank_{i}$	$.316^{**}$
	(.020)
N	8,125
R^2	0.05

Note: ** $p < 0.01$, * $p < 0.05$

Table 6. Results Summary	
Hypothesis	**Result**
H1: As the level of the popularity of a book increases, more reviewers will review the book.	Support
H2: As the level of the crowdedness of a book's review segment increases, fewer reviewers will review the book.	Support
H3a: Reviewers with high reputation costs is more likely to adopt the safe strategy by imitating their ratings.	Support
H3b: Reviewers with low reputation costs is more likely to adopt the risky strategy by differentiating their ratings.	Support

Table 7. Fixed Effects Estimation on Book Choice ($DailyReviewNumber_{it}$)

	Amazon	**BN**	**Amazon & BN**
$SalesRank_{it-1}{}^{\Delta}$	$-.460^{**}$	$-.668^{**}$	$-.668^{**}$
	(.023)	(.051)	(.051)
$ReviewNumber_{it-1}{}^{\Delta}$	$-.073^{**}$	$.473^{**}$	$.473^{**}$
	(.014)	(.031)	(.031)
$PotentialReviewers_{it-1}{}^{\Delta}$	$.165^{**}$	$.129^{**}$	$.129^{**}$
	(.023)	(.036)	(.036)
$DaysElapsed_{it}$	$-.018^{**}$	$-.036^{**}$	$-.036^{**}$
	(.001)	(.002)	(.002)
$AmazonSalesRank_{it-1}{}^{\Delta}$			$.207^{**}$
			(.056)
$AmazonReviewNumber_{it-1}{}^{\Delta}$			$-.547^{**}$
			(.035)
$AmazonPotentialReviewers_{it-1}{}^{\Delta}$			.035
			(.043)
$AmazonDaysElapsed_{it-1}$			$.018^{**}$
			(.003)
$Amazon_i$			1.786^{**}
			(.143)
N	40,568	26,533	67,101
Log likelihood	-21627.664	-4981.676	-26609.34

Note: ** $p < 0.01$, * $p < 0.05$
$^{\Delta}$ Variables are normalized using the following formula to allow comparison across two sites. (Variable – Mean)/Std. Dev.

Table 8. Fixed Effects Estimation on Electronic Product Choice ($DailyReviewNumber_{it}$)

Variable	(1)	(2)	(3)
$SalesRank_{i,t-1}$	-.205**		-.247**
	(.019)		(.020)
$ReviewNumber_{i,t-1}$		-.175**	-.301**
		(.042)	(.043)
$PotentialReviewers_{it-1}$	.013**	.027**	.019**
	(.003)	(.004)	(.004)
$DaysElapsed_{it}$	-.002*	-.004**	.001
	(.001)	(.001)	(.001)
N	20,532	20,532	20,532
Log Likelihood	-6461.962	-6506.139	-6436.897

Note: ** $p < 0.01$, * $p < 0.05$

Table 9. SUR Estimation on Choosing Rating/Text Strategies

	$RatingDeviation_{ij}$	$NegTextDeviation_{ij}$
$ReviewerRank_{ij}$	.010**	.000005**
	(.004)	(.000002)
$RealName_{ij}$	-.120**	.000003
	(.046)	(.00002)
$ReviewNumber_{i}$	.316**	.00005**
	(.020)	(.000009)
$SalesRank_{i}$	-.054**	-.000001
	(.008)	(.000004)
$Length_{ij}$		-.0002**
		(.00001)
N	8,125	8,125
R^2	0.05	0.07

Note: ** $p < 0.01$, * $p < 0.05$

Table 10. Alternative Estimations for Cost and Benefit from Differentiation Strategies

Variable	Gaining Attention: *DailyTotalVote$_{ijt}$* (Benefit)	Receiving Negative Feedback: *DailyUnhelpfulVote$_{ijt}$* (Cost)
RatingDeviation$_{ijt-1}$	.056**	.103**
	(.006)	(.009)
SalesRank$_{it-1}$	-.261**	-.359**
	(.007)	(.011)
ReviewNumber$_{it-1}$	-.914**	-1.149**
	(.014)	(.023)
ReviewerExperience$_{ijt-1}$	-.141**	-.142**
	(.011)	(.021)
RealName$_{ij}$	-.074	.381**
	(.046)	(.082)
DaysElapsed$_{ijt}$	-.013**	-.011**
	(.0004)	(.001)
TotalVote$_{ij,t-1}$	-.002**	
	(.0002)	
TotalUnhelpfulVote$_{ij,t-1}$		-.003**
		(.0003)
N	339,402	228,298
Log Likelihood	-75041.020	-30496.451

Note: ** $p < 0.01$, * $p < 0.05$

Table 11. OLS Estimation on Choosing Rating Strategies

ReviewerExperience$_{ij}$	-.118**
	(.009)
RealName$_{ij}$	.019
	(.045)
ReviewNumber$_{i}$	.278**
	(.020)
SalesRank$_{i}$	-.045**
	(.008)
N	8,125
R^2	0.06

Note: ** $p < 0.01$, * $p < 0.05$

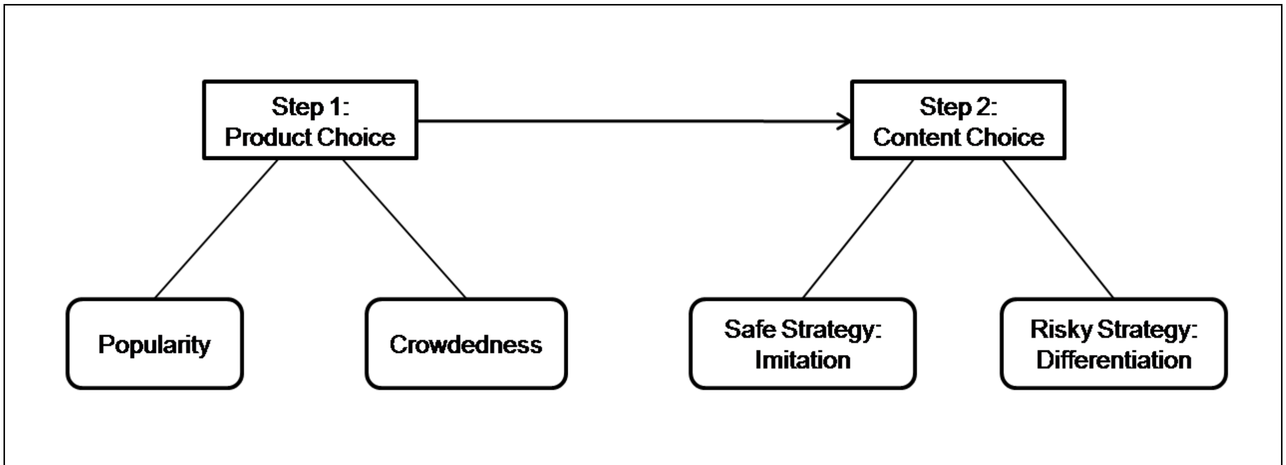

Figure 1. Research Framework

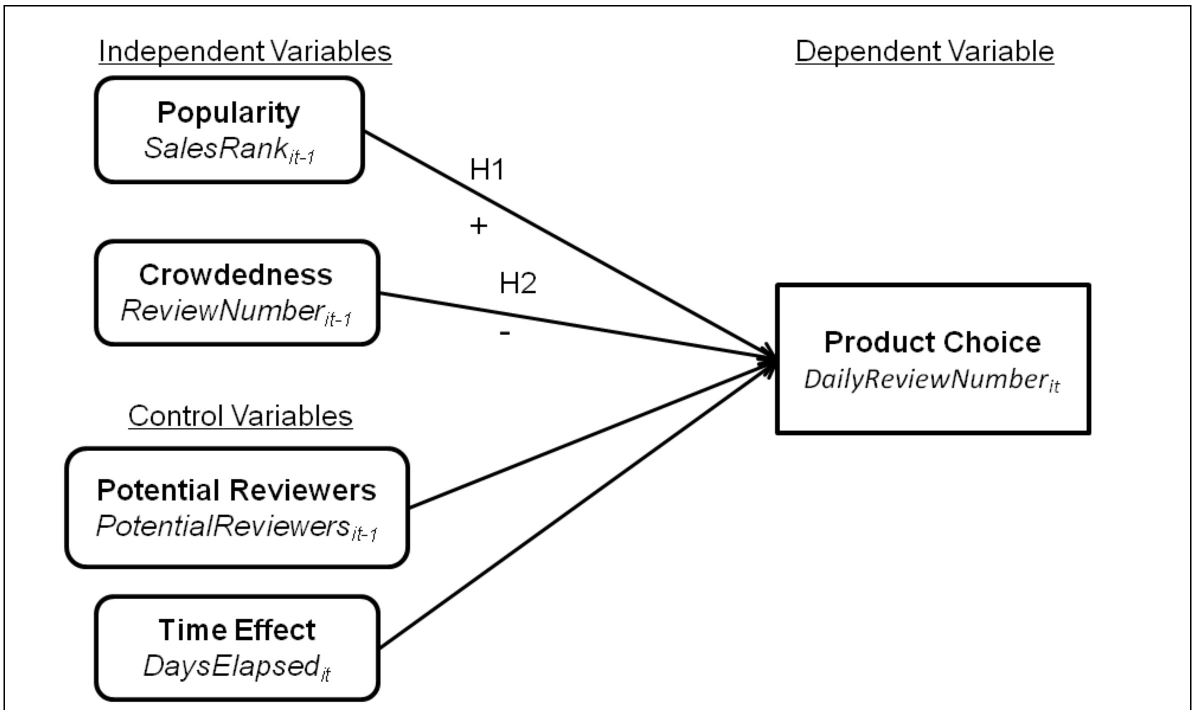

Figure 2. Variables in the Model for Testing H1 and H2