An Empirical Study on How Third-Party Websites Influence the Feedback Mechanism between Online Word-of-Mouth and Retail Sales

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Abstract

Firms use social media marketing to promote products and collect consumer feedback for the product development process. Their practice of investing in retailer-hosted Word-of-Mouth (internal WOM) is supported by a positive feedback mechanism between internal WOM and retail sales. Internal WOM is a sales influencer: consumers can get informed about a product by a large volume of internal WOM. It is also a sales outcome: greater past sales lead to more WOM. Beyond internal WOM, consumers are shown to search widely for product information on third-party websites. Consequently, many firms also start to invest in content on third-party websites. However, little is known regarding the interplay between internal WOM and the contents of third-party websites, which have both been invested in by firms in recent years. In the context of the online software market, this study examines how WOM hosted by third-party websites (external WOM) and third-party free sampling influence the feedback mechanism between internal WOM and retail sales. Using data from Download.com and Amazon.com, we analyze the impact via a simultaneous equation model in a Bayesian hierarchical framework. We find that external WOM and third-party free sampling moderate the sales-outcome role of internal WOM in different ways. Receiving external user reviews amplifies the impact of past sales on volume of internal WOM; whereas third-party free sampling weakens the impact of past sales on internal WOM. Moreover, this impact of external WOM and third-party free sampling on the sales-outcome role of internal WOM is much more significant than their impact on the sales-influencer role of internal WOM.

Keywords: Online Word-of-Mouth; online user review; third-party website; free sampling; retail sales; software market

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1. Introduction

E-commerce sales for the second quarter of 2013 were $64.8 billion, an increase of 18.4 percent compared to the same quarter of 2012 [1]. The convenience of shopping online anywhere, anytime is tremendous. Consumers tend to collect extensive product information on the Internet to assess product quality before they make purchase decisions [2, 3, 4, 5, 6, 7], since online shopping is unable to provide physical experience or examination of the product. This phenomenon is especially prominent in the market for experience goods, whose quality is difficult to evaluate. Consumers have been shown to utilize online Word-of-Mouth (WOM) information hosted by retail websites (*internal WOM*) [5] where they are going to purchase [8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20], including internal user reviews.

Consequently, firms have widely embraced online social media, mainly for two purposes: to promote products to enhance sales, and to collect consumer feedback to benefit product development. In addition to creating online buzz, WOM carries the wisdom of the crowd and thus becomes an economic way for firms to assess customer satisfaction and operations by extensively listening to consumers. Today, the budget for social media marketing accounts for about one-quarter of the entire marketing budget [21]. Firms have been encouraging and managing user-generated content on retail websites, a practice that is generally supported by research findings [8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20]. Recently many firms have started to more aggressively utilize social media by investing in content on third-party websites, in addition to retailer-hosted content [22]. To probe for product quality of experience goods, consumers also resort to richer and more widely available WOM information hosted by third-party websites (*external WOM*), which are online agents that accumulate and disseminate product information [4, 5, 6]. In support of this emerging practice, empirical evidence has shown that external user reviews can be more influential on sales than internal user reviews when those two WOM sources are examined simultaneously but independently [5].

However, while firms are putting resources into both retail websites and third-party websites, there is an unresolved question regarding how their inputs to third-party websites influence their WOM marketing efforts on retail websites. The extant literature does not fully account for firms' investment in third-party websites, in the context of their marketing efforts to solicit internal WOM. First, little is known regarding how the availability of external WOM can affect the dual roles that internal WOM plays in retail websites, specifically its sales-influencer role and its sales-outcome role [8, 9, 12, 17, 19]. The amount of WOM conversations on retail websites, defined as the volume of internal WOM, is demonstrated to be a sales influencer. A larger volume of online WOM increases consumer awareness of the product, leading to a higher possibility of purchase. In addition to this sales-influencer role, the volume of internal WOM is also a sales outcome. Greater past sales imply a larger number of reviewers, leading to more user-generated WOM [12]. In other words, there exists a positive feedback mechanism between internal WOM and retail sales. Therefore, it is natural to ask, when consumers can find reviews from sources outside of the retail websites, will they rely less on internal WOM than they do in the absence of external WOM? Will they become less willing to write post-purchase reviews on retail websites in the presence of external WOM?

Second, firms also need to be aware that third-party websites not only solicit external WOM, but also generally offer free sampling in a digital format to allow consumers to directly experience products free of charge. For example, consumers can try out software programs, either with limited functionality or for a limited period of time, on CNET Download.com (CNETD); Amazon.com (Amazon) provides free preview of some chapters for selected books; iTunes stores offer free songs and free videos from broad categories. Therefore, there is also a need to understand the potential interplay between free sampling on third-party websites and internal WOM on retail websites.

To shed some light on this issue, this study investigates how external WOM and third-party free sampling influence the dual role of internal WOM: the sales-influencer role and the sales-outcome role. We capture external WOM and free sampling by measuring whether a product receives WOM on third-party websites, and how many free samples are adopted by consumers, respectively. Accordingly, we aim to address the following two main research questions: (1) do providing external WOM and encouraging consumer use of free sampling on third-party websites influence how internal WOM affects sales?; and (2) do they also influence the impact of past sales on internal WOM?

To answer those two questions, we collected panel data on software programs over 14 weeks, including external WOM and free sampling information from a third-party website, CNETD, and the sales and user review information from Amazon. We used a simultaneous equation model in a Bayesian hierarchical framework to capture the feedback mechanism between internal WOM and retail sales, and the moderation effect of third-party contents. We found that both external user reviews and free sampling on third-party websites influence the sales-outcome role of internal WOM. Receiving CNETD user reviews enhances the positive impact of Amazon past sales on the volume of Amazon user reviews. For example, for an Amazon software program with average weekly sales of 10 copies, receiving user reviews on CNETD can result in one additional Amazon user review. On the contrary, we found a negative moderation effect of third-party free sampling on the sales-outcome role of internal WOM. More downloads of free-trial software on CNETD weaken the impact of Amazon sales on the volume of Amazon user reviews. For instance, an Amazon software program with average weekly sales of 10 copies can have two additional Amazon user reviews if its CNETD free-trial version receives only one weekly download, compared to the number of Amazon reviews it would receive in the case of 1,000 CNETD weekly downloads. However, we found that external WOM and third-party free sampling do not significantly influence the sales impact of internal WOM. Our robustness check demonstrates that this impact can be mistakenly interpreted as significant, if the empirical estimation omits the impact of external WOM and third-party free sampling on the sales-outcome role of internal WOM. These results highlight the importance of examining the whole loop between internal WOM and retail sales in this line of research.

Therefore, our findings indicate that firms' investments in content on third-party websites affect their efforts on retail websites for soliciting WOM, but do not affect consumers' reliance on internal WOM during purchase decision making. Specifically, our results encourage firms to adopt advanced Internet technologies, for example, Web 2.0, to engage consumers in online WOM on third-party websites. Firms' investment in content on third-party websites for encouraging user-generated WOM can significantly amplify their parallel effort at encouraging consumer feedback on retail websites. The larger amount of feedback across the platforms, as a result of having external user reviews available on a third-party website, benefits firms in promoting sales and collecting consumer suggestions. Those suggestions are important for firms to improve existing products and develop new products. Nevertheless, firms should be careful with excessively promoting free sampling on third-party websites. Our results caution that third-party free sampling can be counterproductive to firms' WOM marketing strategy on retail websites. More use of free samples tends to create less incentive for consumers to share their thoughts after purchase. As a result of less active online WOM participations, encouraging third-party free sampling can also hinder firm's assessment of product and service quality, and their new product development.

The rest of paper proceeds as follows. The next section reviews the relevant literature and presents the research model. We then describe the data and analyze the empirical model. In the last section, we discuss the results and research implications, and conclude the paper by addressing the limitations and identifying areas for future research.

2. Related Literature and Research Model

In this section, we review the related literature, and present our research model. Our work is mainly related to two streams of prior research: (1) studies of the online WOM effect, and (2) studies of why consumers contribute to online WOM activities after purchase.

2.1 Online WOM effect

Most of the existing research examines the economic impact of online WOM by focusing on WOM information generated by a single type of reviewer (consumers, experts, sellers, or providers). For example, extant studies have agreed on the significant relationship between professional reviews and consumer decisions, because professional reviews are provided by experts to build up reputation, offer product information, and serve as advertisements [23, 24, 25, 26, 27]. More extensive studies have been conducted to examine user-generated WOM, specifically user reviews [9, 10, 11, 12, 13, 14, 15, 17]. Despite divergent conclusions on other measures of WOM, WOM volume, which is commonly measured by the number of online user reviews, has been shown to significantly improve market outcome [2, 17]. The larger volume of user reviews can better attract consumers' attention to the product and accordingly result in a higher chance of choosing it [14, 17].

Recent studies identify a more intricate relationship between volume of internal WOM and retail sales, which can be summarized by a positive feedback mechanism [14]. In addition to its influence on sales, internal WOM is also an outcome of retail sales. This assertion is further explicitly supported by an empirical study [12] that movie revenues positively influence volume of online WOM, which in turn influences box office performance. The volume of internal WOM depends on the number of reviewers, which can be inferred by retail sales, so it is endogenous in nature. In sum, internal WOM has a sales-influencer role that it has a positive impact on sales; it also has a sales-outcome role that it is generated by consumers after purchase. However, most WOM studies focus on the sales-influencer role of internal WOM alone [8, 9, 15, 20]. Our study contributes to the understanding of internal WOM by investigating the moderators on the dual roles of internal WOM.

In addition, extant studies mostly investigate the sales impact of internal WOM without considering the existence of relevant product information hosted by third-party websites, such as external WOM and free sampling, although the industry cannot delay putting marketing resources into this third-party content [22]. Two recent studies incorporate one of the most important types of content on third-party websites, external WOM, into this line of research by comparing the differential impact of internal and external WOM [5, 28]. Senecal and Nantel [28] studied one special type of online WOM information—product recommendations on both third-party websites and retail websites. They found that external product recommendations are more influential on consumers' online choices than internal product recommendations. Gu et al. [5] found similar results regarding online user reviews hosted by retail and third-party websites in the context of high-involvement products.

The common underlying assumption of those two studies is that external WOM and internal WOM independently influence retail sales. In addition, neither of those two studies examined free sampling, which is prevalent and has become one of the most important features on third-party websites in recent years. Beyond soliciting WOM, many vendors offer free product sampling of experience goods on third-party websites, such as free software downloads on CNETD and free movie previews on IMDB.com, because people can hardly assess the product quality of experience goods before consumption [29]. Our study contributes to this line of research by testing not only the interplay of internal WOM and external WOM, but also the interplay of internal WOM and third-party free sampling. Free sampling helps consumers reduce uncertainty about product quality through direct experience, while external WOM serves as an indirect exposure to others' experience [29, 30]. Therefore, we are interested in further studying whether and how they differentially affect the positive feedback mechanism between internal WOM and sales.

This study also contributes to the online WOM literature by showing that the influence of external WOM and third-party free sampling on the sales-outcome role of internal WOM is more significant than on the sales-influencer role of internal WOM. We find empirical evidence that the moderation effect of external WOM and third-party free sampling becomes insignificant, once their moderation effect on the sales-outcome role of internal WOM is captured.

2.2 *Why do consumers participate in online WOM after purchase?*

The second stream of literature relevant to our work concerns the motivation for consumers to write reviews online after purchase. There are two main theories regarding the generation of online WOM that have been empirically supported: self-enhancement theory and review environment theory. Self-enhancement theory is relatively traditional, extending offline WOM theory into the online context. It looks into the psychological drivers behind users' sharing behavior. Users have been shown to share their experiences online for self-enhancement [31, 32]. Self-enhancement is defined as users' emotional desires to gain attention and enhance their images among others [31, 33]. Therefore, self-enhancement theory implies that consumers can be less willing to share their feedback on products, if they perceive a smaller chance for others to recognize their contributions and enhance their images in the online community. Our study contributes to this line of research by identifying the impact of third-party websites on consumers' likelihood of sharing experience online.

Review environment theory argues that users' decisions to post reviews are subject to environmental factors, such as others' opinions [34, 35]. Our study empirically validates this more recent theory by showing external WOM and third-party free sampling as important environmental factors that affect consumers' decisions of whether to post feedback online. Consumers resort to external WOM and third-party free sampling before arriving at a retail website [5], and this characterizes the consumers' rating environment on retail websites. Moreover, we also show the difference in moderation effect between external WOM and third-party free sampling.

2.3 *Research model*

Based on the above literature review, we propose that external WOM and third-party free sampling moderate the positive feedback mechanism between internal WOM and sales, illustrated by Figure 1.

Insert Figure 1 about here

Third-party websites often provide professional reviews on selected products, in addition to hosting reviews generated by users. Compared to user reviews, professional reviews created by experts provide more authoritative judgments by precluding personal biases to some degree [24]. However, unlike user reviews, experts are a smaller group of people and thus can apply their expertise to review only a small fraction of the products available on the market. Hence, it is interesting to examine whether receiving external WOM generated by those two distinct reviewer identities, namely experts and users, has a differential impact on the feedback mechanism on retail websites. In addition, we also expect that free sampling affects the feedback mechanism differently from external WOM. External WOM and free sampling are different in providing product information. The former offers product information indirectly through prior consumers' experiences; the latter allows consumers to directly try the product by themselves [29, 30]. Therefore, we explicitly examine external WOM, including professional reviews and user reviews, and free sampling as the contents of third-party websites. Below, we explain our research model in detail.

We propose a two-way moderation effect of external WOM and third-party free sampling on the feedback mechanism on retail websites. We first look into the sales impact of internal WOM. The volume of internal WOM influences consumer awareness as a cognitive consequence, which in turn affects ultimate consumer choices [17]. The more internal WOM activities a product receives, the more likely consumers may get informed about it on retail websites, thus leading to greater retail sales [14, 17]. We propose that external WOM and third-party free sampling may negatively influence this positive sales impact of internal WOM. First, receiving user reviews and professional reviews on third-party websites helps create online buzz about the product, so that it is more visible on the market than if it was not reviewed on third-party websites. Therefore, consumers rely less on internal WOM to be aware of the product. Second, according to Hansen's psychological choice model [36], consumers' reliance on WOM has been shown to depend on contextual factors, such as product variety, product popularity, and consumer Internet experience in the online context [19, 20, 37]. Because consumers are shown to visit third-party websites for product information during their purchase decision making on retail websites [5, 6], the content of third-party websites functions as a contextual factor to moderate the sales impact of WOM.

Following the same argument, we also propose that free sampling negatively moderates the sales impact of internal WOM. More consumer use of free sampling on third-party websites also help make the product stand out from the crowd. In addition, greater use of free sampling indicates that more consumers have already directly experienced product quality [30]. Therefore, consumers rely less on internal WOM for being informed about the product and search less for product information via internal WOM.

We also propose that external WOM and third-party free sampling moderate the positive impact of sales on internal WOM. The volume of internal WOM is the outcome of retail sales [12, 17]. The underlying rationale is that the sales number implies the number of reviewers, who write reviews after purchase. The greater the sales, the larger the number of reviewers. Specifically, the number of reviewers can be approximately captured by *(consumer base)*(consumer's likelihood to write reviews)*. More reviewers tend to generate more user reviews, indicating the sales-outcome role of internal WOM. In other words, the impact of sales on the volume of internal WOM depends on two factors: the consumer base and consumers' likelihood to participate in WOM activities. For a given level of consumer likelihood to participate in post-purchase WOM activities, greater sales imply a larger consumer base and accordingly more potential reviewers, leading to more user feedback. Once there is a change in consumer's likelihood to share opinions, the impact of sales on volume of internal WOM would change.

As discussed in Section 2.2, review environment theory implies that environmental factors can influence consumer decisions on whether to share [35]. Consumers are shown to visit third-party websites during their purchase decision making [5, 6]. The content on third-party websites, including external WOM and free sampling, can be interpreted as environmental factors in consumers' review decisions. As a result, external WOM and free sampling may influence consumer's likelihood of writing reviews. Because the impact of sales on the volume of internal WOM depends on consumer's likelihood to contribute to WOM on retail websites, this sales-outcome impact is expected to be moderated by external WOM and free sampling as environmental factors.

Self-enhancement theory supports this proposition as well [31]. In addition, it provides more insights into the direction of the proposed moderation effect. In terms of external WOM, we apply this theory and arrive at two competing arguments. The first argument is that external WOM negatively moderates the impact of sales on internal WOM. If the product has already been reviewed on third-party websites, consumers may be aware that others can get even more product information from the larger crowd or the distinct reviewer identity of experts from third-party websites, as compared to retail websites. Therefore, there is a smaller chance that their reviews on retail websites will be read and appreciated by others, should they decide to share opinions. Due to this lower perceived chance of achieving self-enhancement, the likelihood for them to write reviews after purchase is lower [31]. This leads to less significant impact of sales on volume of internal WOM, indicated by a smaller number of reviews (*(consumer base)*(consumer's likelihood to write reviews)*). Hence, external WOM can have a negative moderation effect on the sales-outcome role of internal WOM. The other competing argument, instead, proposes the opposite, that is, a positive moderation effect. Some consumers take receiving external WOM as an indicator of product visibility, since not all products are reviewed on third-party websites. Writing reviews on those eye-catching products has a larger likelihood of making the corresponding reviews visible and thus achieving self-enhancement, compared to reviewing products that have not been reviewed on third-party websites. Consumers thus are more likely to contribute to internal WOM, leading to a positive moderation effect on the impact of sales on volume of internal WOM. Both those two opposite forces can take place, but it is not clear which one dominates. Therefore, we will resort to our empirical analysis to reveal the direction of the moderation effect of external WOM on the sales-outcome role of internal WOM.

In terms of third-party free sampling, self-enhancement theory implies that third-party free sampling negatively moderates the impact of sales on internal WOM. Consumers perceive a low chance for highlighting the value of their reviews and enhancing their images, if many people have already experienced the product on third-party websites. Consumers can get first-hand product information directly via third-party free sampling and thus less likely recognize the value of others' shared experiences. As a result, consumers have a lower likelihood of writing reviews on retail websites. In this case, the impact of sales on internal volume is less significant, which is approximately determined by the number of reviewers (*(consumer base)*(consumer's likelihood to write reviews)*).

3. Data

We conducted our empirical analysis using a panel data set collected over 14 weeks in the online software market. The software market is extraordinarily competitive. Sales of both popular and niche software programs have increased tremendously over the past few years [19]. In 2013, the global software market had a value of $554.5 billion, an increase of 11.3% since 2009, of which the United States accounts for 42.6% [38]. Moreover, software programs, as a typical type of experience goods, are generally difficult for consumers to observe and assess in terms of product quality before consumption. Hence, the abundant product choices and the nature of experience goods require consumers to extensively search for software information before making purchase decisions.

We collected retail sales rank and internal WOM data from Amazon. We choose Amazon to represent the retail website, because Amazon is one of the most well-known e-commerce sites and is also widely adopted in e-commerce research for examining online market outcomes. Consumers can share their feedback on Amazon after purchasing software programs through a five-star rating system. Amazon summarizes user reviews for each product via an overall average rating, a total number of user reviews and the number of user reviews for each rating scale. Therefore, we can easily measure the volume of internal WOM by the total number of Amazon user reviews ($Uservolume_{i,t}^{a}$).

We collected the data on external WOM and third-party free sampling from CNETD. As briefly mentioned above, CNETD is a leading and representative third-party website for reviews and free software downloading. It has a library of over 80,000 free-trial software programs, in the format of free software sampling, for four different platforms, including Windows, Mac, mobile devices, and webware. For each platform on CNETD, there are more than 20 groups of software programs with approximately 6 to 20 categories in each group. CNETD lists detailed product descriptions as well as the number of consumer uses of free sampling, that is, weekly download counts ($Weekdownload_{j,t}^{c}$), for each software program. Similar to Amazon, CNETD users can also post reviews with detailed comments and rate the product on a scale of one to five, with one being the worst and five the best. In addition, CNETD is known for its editorial team, which provides professional reviews for selected software programs (usually popular products) by a similar five-star rating system. As a result, the information regarding third-party free sampling and external WOM is readily available. Because of its large collection of free-trial software programs and WOM information, CNETD is normally displayed among the top three links in the search results of any search engine for software program inquiries. Therefore, we assume that consumers very likely will visit CNETD to try out free-trial software programs and/or look for external WOM information during their information search, if they have intentions to purchase software programs on Amazon.

We collected weekly data on free-trial software programs in three categories listed on CNETD and the corresponding commercial versions sold on Amazon during the period of November 2010 through February 2011. These categories include Antivirus Software, Digital Media Player, and Download Manager, which include categories with different application purposes. We extracted the following information on every software program listed in each of the three categories on CNETD every week: software name, last week's downloads, whether the product received user reviews, whether the product received a CNETD professional review.

Meanwhile, we also collected data on the corresponding Amazon software. We conducted the following matching process. For each software program for which information was collected on CNETD, we input its software name into Amazon's search box in its software department to collect up to 60 most relevant Amazon software programs, which were sorted by Amazon's built-in relevance criteria. We also recorded the sorted ranking as the relevance order of each of those 60 approximately matched Amazon software programs for the searched CNETD free-trial software. Hence, one CNETD free-trial software program can be mapped to 60 or fewer approximately matched Amazon software programs with the relevance order 1 being the most relevant. Although we could not manually check each matched pair every week due to the excessive work load, we were able to observe that each collected Amazon software program was matched to only one CNETD free-trial software program with a relevance order between 1 and 60 over 14 weeks. Therefore, we believe that such a matching process can identify an Amazon software program and its most relevant free-trial version on CNETD. For each Amazon software program, we collected software name, relevance order with respect to the matched CENTD product, sales rank, whether the produce received user reviews, average user rating, total number of user reviews, number of user reviews at each rating level, first available date, price, discount on price, and eligibility for free-shipping service. Since every category represents a unique group of software programs with similar application purposes, we defined each category as a single market and conducted the model estimation in each category [39].

We used Amazon sales rank as the proxy for Amazon sales. Extant studies have identified a Pareto relationship between sales and sales rank in various contexts [5, 40, 41, 42]. In particular, Ghose and Sundrararajan [41] conducted an experiment to estimate the Pareto index as 0.828 and the constant as 8.352 for Amazon software sales, based on the negative log-linear relationship between sales rank and sales. Because we were using the same Amazon software context, we adopted their estimations on the Pareto relationship to infer the log values of actual sales ($Lnsales_{i,t}^{a}$) from the log values of Amazon sales rank ($Lnrank_{i,t}^{a}$) by the following equation: $Lnsales_{i,t}^{a} = -0.828 * Lnrank_{i,t}^{a} + 8.352$.

Following Godes and Mayzlin [14] and Liu [17], we used a one-week lag between independent variables and dependent variables of sales rank and WOM to model the feedback mechanism between Amazon WOM and Amazon sales. This technique reflects the process of consumers' purchase decision making and their subsequent participation in internal WOM activities. The time lag also helps reveal the causality relationship. Therefore, we only kept Amazon software programs that appeared in two consecutive weeks, together with their matched CNETD products. This results in a panel data set over 13 weeks. Table 1 describes our key variables, and Table 2 presents the summary statistics of the variables. The summary statistics show that on average, less than 20% of CNETD products received CNETD professional reviews. This poses a statistical challenge in examining the moderation effect of external professional reviews, which is addressed in the next section.

Insert Tables 1 and 2 about here

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4. Empirical Analysis

In this section, we describe a simultaneous equation model of Amazon WOM and sales with random coefficients modeled by a hierarchical structure in a Bayesian framework and present the estimation results. Specifically, we model two simultaneous equations to capture the feedback mechanism between Amazon WOM and sales. Also, using a hierarchical structure, we explain the sales-influencer and sales-outcome role of Amazon WOM both as a function of CNETD WOM and CNETD downloads of free-trial software. Therefore, the whole model is composed of two simultaneous equations and two hierarchical moderation equations. We assume that the error terms of the two simultaneous equations are correlated and follow a bivariate normal distribution with a mean of zero, in order to capture the endogeneity of Amazon WOM. We apply the Markov Chain Monte Carlo (MCMC) method [43, 44] to empirically estimate the full model with a focus on the moderation effect of CENTD WOM and downloads of free-trial software on the positive feedback between Amazon WOM and sales.

4.1 Empirical model

We built our model in a Bayesian framework as a robust approach to cope with the issue that only a small portion of CNETD free-trial software programs are reviewed by experts. The Bayesian framework has substantial advantages over the classic frequency framework when the sample size is small, which is the case in testing the significance of external professional reviews in this study [39, 40]. The Bayesian framework does not rely on the asymptotic estimations used by the frequency framework. Instead, it calculates exact estimations.

We modeled the feedback mechanism between volume of Amazon user reviews and Amazon sales by two simultaneous equations. Specifically, the first equation (AmazonWOM equation) in the full model uses the volume of Amazon user review ($Uservolume_{i,t}^{a}$) as a dependent variable to model the impact of past sales on internal WOM. Similarly, the second equation (AmazonSales equation) uses Amazon sales rank with a log transformation ($Lnrank_{i,t}^{a}$) as a dependent variable to model the sales impact of internal WOM. The main effects of the sales-outcome role and sales-influencer role of Amazon WOM, when the impact of CNETD website is not considered, are modeled by the coefficients (α_1, β_1) on the single terms $Lnrank_{i,t-1}^{a}$ and $Uservolume_{i,t-1}^{a}$ in equations 1 and 2 respectively. This leads to the following two simultaneous equations:

AmazonWOM equation

$$\begin{aligned} Uservolume_{i,t}^{a} &= \alpha_0 + \alpha_1 * Lnrank_{i,t-1}^{a} + \alpha_{j,t-1}^{c} * Lnrank_{i,t-1}^{a} * (1/Relevance_{i,j,t-1}^{a}) \\ &+ \alpha_2 * Dummyuser_{i,t-1}^{a} + \alpha_3 * Dummyuser_{i,t-1}^{a} * Urating_{i,t-1}^{a} + \alpha_4 * Age_{i,t}^{a} \\ &+ \alpha_5 * Agesq_{i,t}^{a} + \varepsilon_{i,t}^{a} \end{aligned} \tag{1}$$

AmazonSales equation

$$\begin{aligned} Lnrank_{i,t}^{a} &= \beta_0 + \beta_1 * Uservolume_{i,t-1}^{a} + \beta_{j,t-1}^{c} * Uservolume_{i,t-1}^{a} * (1/Relevance_{i,j,t-1}^{a}) \\ &+ \beta_2 * Dummyuser_{i,t-1}^{a} + \beta_3 * Dummyuser_{i,t-1}^{a} * UratingR_{i,t-1}^{a} \\ &+ \beta_4 * Dummyuser_{i,t-1}^{a} * UratingRsq_{i,t-1}^{a} + \beta_5 * Userdispersion_{i,t-1}^{a} + \beta_6 * Age_{i,t}^{a} \\ &+ \beta_7 * Agesq_{i,t}^{a} + \beta_8 * Discountprice_{i,t}^{a} + \beta_9 * Discount_{i,t}^{a} + \beta_{10} * Freeship_{i,t}^{a} + \delta_{i,t}^{a} \end{aligned} \tag{2}$$

$$a: Amazon, \quad c: CNETD, \quad t: Week$$

Since the volume of user reviews is endogenous [12], the errors of the above two equations ($\varepsilon_{i,t}^{a}$ and $\delta_{i,t}^{a}$) are contemporaneously correlated, as specified below [43, 44, 45].

$$\begin{bmatrix} \varepsilon_{i,t}^{a} \\ \delta_{i,t}^{a} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Sigma_{\varepsilon\varepsilon}^{a} & \Sigma_{\varepsilon\delta}^{a} \\ \Sigma_{\delta\varepsilon}^{a} & \Sigma_{\delta\delta}^{a} \end{bmatrix}\right) \quad (3)$$

To capture the moderation effect of CNETD WOM and free sampling on the feedback mechanism, we modeled two random coefficients ($\alpha_{j,t-1}^{c}$, $\beta_{j,t-1}^{c}$) on $Lnank_{i,t-1}^{a}$ *$(1/Relevance_{i,j,t-1}^{a})$ in the AmazonWOM equation and $Uservolume_{i,t-1}^{a}$ *$(1/Relevance_{i,j,t-1}^{a})$ in the AmazonSales equation [45]. The inversed relevance order $(1/Relevance_{i,j,t-1}^{a})$ was added as a multiplier of $Lnrank_{i,t}^{a}$ and $Uservolume_{i,t}^{a}$ in those two equations, respectively. As described in the data section, each Amazon product *i* was matched to the most relevant free-trail software program, CNETD product *j*. Their relevance level was captured by a relevance order ($Relevance_{i,j,t-1}^{a}$) based on Amazon's built-in relevance search criteria. Therefore, it is reasonable to assume that the moderation effect from the information of CNETD product *j* on Amazon product *i* should be more significant when these two products are more relevant. Note that a larger value of $Relevance_{i,j,t-1}^{a}$ implies a weaker relevance; as a result, the inversed relevance order was adopted.

Our research model implies that both of the two random coefficients ($\alpha_{j,t-1}^{c}$, $\beta_{j,t-1}^{c}$) depend on whether the matched CNETD product is reviewed by experts or consumers and how many free samples are already adopted, leading to the following CNETD moderation equations (Equations 3 and 4). The external WOM information of CNETD product *j* is indicated by two dummy variables: whether the CNETD product *j* receives any CNETD user review ($Dummyuser_{j,t-1}^{c}$) and whether this product receives a CNETD professional review ($Dummypro_{j,t-1}^{c}$). Consumer adoptions of free sampling on CNETD are measured by number of weekly downloads. We applied a log transformation on weekly downloads ($weekdown_{j,t-1}^{c}$) in order to convert the value to a comparable magnitude to other variables ($Logweekdown_{j,t-1}^{c}$). Therefore, by estimating the full model (Equations 1 to 5), we can test the moderation effect of external WOM and third-party free sampling on the feedback mechanism between internal WOM and sales, mainly by two pairs of coefficients: three coefficients in Equation 4 ($\gamma_1, \gamma_2, \gamma_3$) and three coefficients in Equation 5 ($\lambda_1, \lambda_2, \lambda_3$).

CNETD moderation equations

$$\alpha^{c}_{j,t-1} = \gamma_1 * Dummyuser^{c}_{j,t-1} + \gamma_2 * Dummypro^{c}_{j,t-1} + \gamma_3 * Logweekdown^{c}_{j,t-1} + \omega^{c}_{j,t-1} \quad (4)$$

$$\beta^{c}_{j,t-1} = \lambda_1 * Dummyuser^{c}_{j,t-1} + \lambda_2 * Dummypro^{c}_{j,t-1} + \lambda_3 * Logweekdown^{c}_{j,t-1} + \upsilon^{c}_{j,t-1} \quad (5)$$

In sum, our full model comprises five equations from Equation 1 through Equation 5. Following previous studies, we also included various control variables in two simultaneous equations 1 and 2. In the AmazonSales equation, we included the Amazon average user rating, since prior studies have shown that user rating may influence consumer choices [9, 12, 19, 46]. Chevalier and Mayzlin [9] also found that the impact of user ratings is not linear. As a result, we applied a linear transformation on $Urating_{i,t-1}^{a}$ and used ($Urating_{i,t-1}^{a}$ *-3*) instead, as 3 is the middle point of the Amazon rating scale. For parsimony, we named the new variable $UratingR_{i,t-1}^{a}$ and included its quadratic term, denoted by $UratingRsq_{i,t-1}^{a}$, to model the nonlinear impact of Amazon average user rating. Moreover, Godes and Mayzlin [14] found that dispersion of WOM measured by entropy significantly affects online user choices. Thus we also included the dispersion of Amazon user reviews $Userdispersion_{i,t-1}^{a}$ in the AmazonSales equation, calculated by

$$-\sum_{n=1}^{5} \frac{UservolumeN_{i,t,n}^{\ a}}{\sum_{m=1}^{5} UservolumeN_{i,t,m}^{\ a}} \log\left(\frac{UservolumeN_{i,t,n}^{\ a}}{\sum_{m=1}^{5} UservolumeN_{i,t,m}^{\ a}}\right)$$

, where $UservolumeN_{i,t,n}^{\ a}$ is the number of Amazon *n*-star user ratings. In addition, price effects are controlled by the current price after discount $Discountprice_{i,t-1}^{a}$ and the discount, $Discountp_{i,t-1}^{a}$. A dummy variable $Freeship_{i,t-1}^{a}$ was also included to control for the difference in availability of free-shipping service. We also used product age $Age_{i,t}^{a}$ and the quadratic term of product age $Agesq_{i,t}^{a}$ to control for product diffusion [39]. Those two terms were also included in the AmazonWOM equation, in addition to the Amazon average user rating ($Dummyuser_{i,t-1}^{a}$, $Urating_{i,t-1}^{a}$), as suggested by Duan et al. [12].

4.2 Results

We estimated the above full model in each category using MCMC method. MCMC is a widely adopted computational simulation method in Bayesian statistics, used especially for its applications in estimating hierarchical models [45, 47]. It constructs a large number of Markov chains whose stationary distribution approximates the posterior distribution of the unknown parameter. The posterior mean of the unknown parameter is thus approximately calculated by the mean value of the Markov chains that converge to the stationary. A Gelman-Rubin diagnostic (BGR) is normally used to test the convergence of MCMC draws [43, 48]. Specifically, we used a burn-in of 15,000 MCMC draws to reach convergence, as supported by the BGR measure [43]. Therefore, we used an additional 15,000 target draws to characterize the posterior distribution of the parameters. We used vague priors for all parameters [43]. Table 3 presents the estimation results in each category by posterior means and credible intervals.

Insert Table 3 about here

As expected, we found a positive feedback mechanism between volume of Amazon reviews and Amazon sales. Specifically, the impact of Amazon sales on the volume of Amazon user reviews is significantly positive, indicated by the significant negative α_1 on $Lnank_{i,t-1}^{a}$, given the negative log-linear relationship between sales rank and sales. Similarly, the negative β_1 on $Uservolume_{i,t-1}^{a}$ implies the positive sales impact of volume of Amazon reviews. Therefore, the main effects in the AmazonWOM and AmazonSales equations demonstrate a positive feedback mechanism between internal WOM and online retail sales, which is consistent with findings in prior studies [12].

The two sets of three parameters in the CNETD moderation Equations 4 and 5 are the key to answer whether and how external WOM and third-party free sampling influence the feedback mechanism between internal WOM and sales. We found that both γ_1 and γ_3 in the first moderation equation (Equation 4) are significant. This indicates that, as expected, CNETD user-generated WOM and free downloading moderate the positive impact of retail sales on internal WOM. However, the direction of their moderation effects is different. The coefficient on $Dummyuser_{j,t-1}^{c}$ (γ_1) is significantly negative. Given the negative log-linear relationship between sales and sales rank, this shows that receiving external user reviews positively moderates the impact of Amazon sales on the volume of Amazon reviews. It supports the second argument proposed in our research model that consumers perceive receiving reviews from prior users on third-party websites as a popularity signal. Thus, reviews of those relatively popular products on retail websites have a larger chance to be visible and more likely enhance the corresponding reviewers' image in online community. This leads to a larger likelihood for customers on retail websites to write reviews on those products that have received reviews on third-party websites. Accordingly, the impact of sales on volume of internal WOM is amplified, as it depends on consumer's likelihood of writing post-purchase reviews. To provide an intuitive interpretation of the magnitude of this impact, we adopted Pareto estimations from the study of Ghose and Sundararajan [41] to infer sales from sales rank, as explained in the data section. Receiving CNETD user reviews can lead to more Amazon user reviews of around $60\%*Lnsales_{i,t}^{a}$ than not being reviewed on CNETD. For example, an Amazon software program ranked at 440 is estimated to receive average weekly sales of 10 copies, indicating 10 consumers at most in the past week. If this software program is reviewed by CNETD users, it will receive one additional Amazon review from one of those up to 10 consumers. It shows that the magnitude of such moderation effect is actually very significant for unpopular software. The magnitude for relatively popular products, instead, tends to be less prominent. For example, an Amazon software program ranked at 150 should approximately receive average weekly sales of 25 copies [41]. Receiving CNETD user reviews can lead to two more Amazon user reviews from consumers, who purchased 25 copies in total in the past week.

On the contrary, supporting our research model, CNETD software downloads were shown to have a negative moderation effect on the sales-outcome role of internal WOM, indicated by the positive γ_3. When more people have tried out free sampling, consumers perceive a lower likelihood of achieving self-enhancement by writing reviews on retail websites and are thus more hesitant to share their feedback. Other consumers can directly experience the product through free sampling and thus will not take user reviews as substantial help, merely learning about products indirectly from strangers' experiences. Accordingly, the lower likelihood of sharing on retail websites as a result of more free sampling uses indicates a less significant impact of sales on internal WOM. To show the magnitude of this moderation effect, we compared two scenarios: one weekly download of free-trial software on CNETD versus 1,000 weekly downloads, all else being equal. The volume of Amazon reviews is $72\% {}^{*} Lnsales_{i,t}^{a}$ times larger in the first scenario, using the Pareto index estimated by Ghose and Sundararajan [41]. For an Amazon software program with weekly sales of 10 copies, this difference in volume of Amazon user reviews can be quite substantial, as large as almost two.

In terms of external professional reviews in Equation 4, we found the coefficient on $Dummypro_{j,t-1}^{c}$ (γ_2) to be insignificant in most categories. This implies that, unlike with external user-generated WOM, receiving external professional reviews does not influence the sales-outcome role of internal WOM. It is reasonable to suspect that the two competing forces implied by self-enhancement theory may offset each other. Therefore, on average, consumers do not care about whether experts have reviewed the product on third-party websites when deciding whether to contribute to internal WOM. Another potential explanation could be that consumers recognize that the external professional reviews are written by a reviewer identity that is distinct from that of the consumer. Therefore, they do not perceive external professional reviews either as potential competitors with the reviews they are going to leave on retail websites or as indicators of the popularity of the corresponding product for making internal WOM visible.

We found that all coefficients ($\lambda_1, \lambda_2, \lambda_3$) on the second moderation equation (Equation 5) were nonsignificant in most categories. Neither external WOM nor third-party free sampling significantly moderates the sales impact of internal WOM. This is partly inconsistent with our proposed research model. It indicates that third-party websites do not directly influence consumer's reliance on internal WOM; instead, they affect the amount of internal WOM that are generated by consumers on retail websites, which may indirectly affect sales, given the feedback mechanism between internal WOM and sales. To interpret this result in-depth, we estimated another alternative Bayesian model that comprises Equations 1, 2, 3, and 5 only, using similar MCMC methodology and priors. We intentionally removed Equation 4 so that the moderation effect on the sales-outcome role of Amazon WOM was not captured. We found that λ_1 and λ_3 became significant, which is the only change in the estimation results of this alternative model, compared to the full model. Hence, we conclude that the moderation effect on the sales-outcome role of internal WOM is much more significant than the moderation effect on the sales-influencer role of internal WOM. Third-party websites influence consumers' motivation to share feedback after purchase on retail websites a lot more than they influence consumers' reliance on internal WOM. Therefore, when we separate the sales-outcome role of internal WOM from the sales-influencer role of internal WOM in testing the moderation effect, we find that third-party websites do not interfere with the ability of internal WOM to directly affect sales. This empirical comparison also highlights the importance of studying the moderation effect of third-party websites on the whole feedback mechanism that occurs on retail websites.

We observed a significant covariation between the error terms of the AmazonWOM and the AmazonSales equations. $\sum_{\varepsilon\delta}^{a}$ is significant and thus demonstrates the endogeneity of Amazon WOM, which is consistent with findings from prior studies [12, 17]. We also checked the robustness of our results by first considering the contemporaneous correlation between the error terms of the two CNETD moderation equations (Equations 4 and 5). The error terms of those two equations may have factors in common that were overlooked, for example, content from other third-party websites. The results show that the correlation between the two error terms is nonsignificant, suggesting that those two equations are unrelated and our estimated moderation effect is unbiased. In addition, we also suspect that CNETD free sampling could have a nonlinear moderation effect, instead of the linear impact captured in the full model. Accordingly we estimated a model by adding a log value of the quadratic term of $weekdown_{j,t-1}^{c}$ in the two CNETD moderation equations (Equations 4 & 5) respectively ($Log(weekdown_{j,t-1}^{c})^{2}$). The estimations indicate a nonsignificant nonlinear impact of CNETD free sampling, which adds to the robustness of our full model results[1].

[1] The detailed statistical report of the robustness check is available upon request.

5. Conclusions, Discussion and Future Research

In this paper, we have investigated two major issues that are essential for firms that design social media marketing strategies to boost sales and collect consumer feedback for assessing products and service. We proposed and empirically investigated the impact of external WOM and third-party free sampling on the positive feedback mechanism between internal WOM and sales. We also looked into the difference in such impact between external WOM and third-party free sampling. To do so, we collected weekly panel data from Amazon and CNETD to systematically model the feedback mechanism by simultaneous equations and capture the moderation impact of third-party websites, using a hierarchical structure in the Bayesian framework.

Our results show that the availability of external user reviews has a positive moderating effect on the sales-outcome role of internal WOM that is different from the negative moderating effect of third-party free sampling. Receiving user reviews on third-party websites helps amplify the impact of past sales on volume of user reviews generated on retail websites. An Amazon software program ranked at 440 with an average weekly sales of 10 copies can receive one additional Amazon user review, if it has been reviewed by CNETD users. The impact for more popular products seems less prominent. All else being equal, if this Amazon software program jumps to a sales rank of 150 by selling 25 copies weekly, receiving CNETD user reviews can lead to two additional Amazon user reviews from consumers who purchased a total of 25 copies in the past week. However, receiving external professional reviews does not influence the impact of sales on internal WOM. This indicates that, on average, customers' willingness to share feedback on retail websites is not changed by the existence of reviews created by a distinct identity—experts.

In contrast, third-party free sampling negatively moderates the impact of sales on internal WOM. More uses of free sampling on third-party websites tend to offer a weaker incentive for consumers to leave their comments on retail websites after purchase, leading to fewer reviewers conditional on sales. An Amazon software program with weekly sales of 10 copies is likely to receive two additional Amazon user reviews if its weekly number of downloads on CNETD is one, compared to the number of Amazon user reviews it would receive in the case of 1,000 CNETD weekly downloads. Interestingly, we find that external WOM and third-party free sampling do not affect the sales impact of internal WOM, once their moderation effect on the sales-outcome role of internal WOM is captured. Therefore, we conclude that external WOM and third-party free sampling may indirectly affect online retail sales by moderating the impact of sales on internal WOM.

Our findings make some important contributions to the literature. First, our empirical investigation highlights the importance of studying the whole loop between WOM and retail sales to investigate the impact of the content on third-party websites on internal WOM. Considering either the sales-influencer role or the sales-outcome role of WOM solely can result in misleading conclusions. We found that the impact of external WOM and third-party free sampling on the sales impact of WOM is trivial, in the presence of their impact on the sales-influencer role of WOM. If the latter is not captured, external reviews and third-party free sampling would be mistakenly believed to significantly moderate the sales impact of internal WOM. This study also adds to the understanding of the feedback mechanism between online WOM and retail sales by identifying its contingent relationship with the contents of third-party websites.

Second, this paper also brings important extensions to the WOM literature by identifying the interaction between internal WOM and external WOM. Limited research has examined those two sources of WOM information together. Two recent studies shed some light on this issue by comparing the impact of internal WOM and external WOM [5, 28]. They assume that online user reviews and product recommendations from both retail and third-party websites independently influence retail sales. Moreover, they do not explicitly capture the sales-outcome role of internal WOM. However, our results imply that external user-generated WOM may indirectly affect retail sales through its impact on the generation of internal WOM. Moreover, this paper also cautions that external WOM created by different reviewer identities can have different interactions with internal WOM. Unlike the case with external user reviews, consumers are not influenced by external professional reviews in deciding whether to spread their words online, and hence the impact of sales on internal WOM does not depend on external professional reviews.

Third, this study contributes to the literature on free product sampling. Thanks to advanced Internet technologies, for example, Web 2.0, clouding, and broadband Internet, the online platform now allows firms to efficiently distribute free samples. In particular, in our research context, the marginal production cost of software programs is almost zero; therefore, online free sampling is also an economical approach to promote products by extensively offering direct user experience with the product. However, previous studies have debated over whether free product sampling enhances sales or cannibalizes demand [49]. Our results offer a potential explanation for the cannibalization effect of free sampling from the social media point of view. The use of free sampling on third-party websites can discourage consumers from writing about their experience on retail websites. This can result in less user-generated WOM and accordingly weaker product visibility, leading to a potential negative impact on online sales.

This study has several limitations. First, our conclusions are supported by the empirical analysis of online software data and, therefore, should be extended to other contexts with caution. Consumer behavior for software programs, as one specific type of experience goods, can be different from consumer behavior for other types of goods to some degree [50]. Therefore, it would be interesting to extend this study to a broader context with more product types involved. Second, our study uses data from one single third-party website, CNETD, to study the impact of external WOM and free sampling on the feedback mechanism between internal WOM and retail sales. Consumers are very likely to visit CNETD if they ever choose to resort to any third-party websites for product information of software programs, because of CNETD's dominant position among third-party software sites. Nevertheless, consumers can certainly search on other third-party websites before proceeding to Amazon. Thus it would be interesting to compare the impact of different third-party websites on the feedback mechanism on retail websites. Third, another future research direction is to quantify and compare the potential positive and negative impact of digital free sampling on the sales. Consumers can be encouraged to buy products as a result of their pleasant trial experience; they can also be satisfied with the trial versions and lose their purchasing needs. However, our current research design can only measure the offset effect of free sampling, and therefore cannot compare the magnitude of these two competing impacts. We find that the free sampling doesn't affect sales directly. Specifically, it does not influence consumers' reliance on internal WOM. One of the reasons can be that the negative sales impact of free sampling completely offsets its positive impact. Separating those two competing impacts to measure their sales impact individually can bring in a more in-depth understanding of digital free sampling in E-commerce. Last but not least, although the literature suggest that consumers conduct information searches on both third-party websites and retail websites, we did not directly observe consumer behaviors across websites. A promising extension of this study could look into consumer click-through data to study the phenomenon at the level of the individual consumer.

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Figures

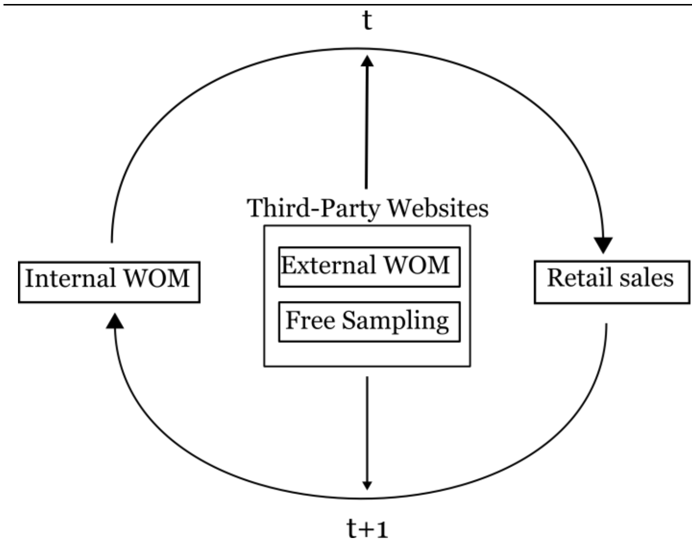

Figure 1. Research model

Tables

Table 1. Description of Key Variables

CNETD (upper *c* denotes CNETD)	
$Dummyuser_{j,t}^{c}$	1 if software *j* receives any user reviews by week *t*; 0 otherwise
$Dummypro_{j,t}^{c}$	1 if software *j* receives CNET professional review by week *t*; 0 otherwise
$Weekdownload_{j,t}^{c}$	Weekly number of downloads of software *j* at week *t*
Amazon (upper *a* denotes Amazon)	
$Lnrank_{i,t}^{a}$	Sales rank of software *i* at week *t* with a log transformation
$Uservolume_{i,t}^{a}$	Total number of user reviews of software *i* by week *t*
$Dummyuser_{i,t}^{a}$	1 if software *i* receives any user reviews by week *t*; 0 otherwise
$Urating_{i,t}^{a}$	Average user rating of software *i* by week *t*
$UservolumeN_{i,t,n}^{a}$	Number of *n*-star user ratings of software *i* by week *t*
$Relevance_{i,j,t}^{a}$	The relevance order of software *i* with its matched CNETD product *j* at week *t*
$Age_{i,t}^{a}$	Days since software *i* has been posted by week *t*
$Discountprice_{i,t}^{a}$	Discount price of software *i* at week *t*
$Discount_{i,t}^{a}$	Discount of software *i* at week *t*
$Freeship_{i,t}^{a}$	1 if software *i* is eligible for free shipping at week *t*; 0 otherwise

Table 2. Summary Statistics of Key Variables

	M	SD	M	SD	M	SD
	Antivirus (N = 8,030)		Windows Media Player (N = 8,754)		Download Manager (N = 4,121)	
Average # of CNETD products	70.154	1.951	122	3.493	40.308	2.097
$Dummyuser_{j,t-1}{}^{c}$	.735	.442	.531	.499	.632	.483
$Dummypro_{j,t-1}{}^{c}$	.185	.389	.138	.345	.141	.349
$Weekdownload_{j,t-1}{}^{c}$	5717.565	54381.82	883.493	4784.84	2175.33	16729.02
Average # of Amazon products	617.692	37.075	795.818	34.257	317	24.759
$Lnrank_{i,t-1}{}^{a}$	8.140	1.727	8.196	1.705	7.278	1.984
$Lnrank_{i,t}{}^{a}$	8.137	1.727	8.184	1.701	7.289	1.997
$Uservolume_{i,t-1}{}^{a}$	29.210	57.522	20.324	46.717	44.727	73.758
$Uservolume_{i,t}{}^{a}$	29.760	57.429	20.585	46.032	46.015	75.391
$Dummyuser_{i,t-1}{}^{a}$	.689	.463	.676	.468	.808	.394
$Urating_{i,t-1}{}^{a}$	2.199	1.7126	2.217	1.747	2.776	1.559
$Relevance_{i,j,t-1}{}^{a}$	20.827	16.801	21.031	16.706	22.595	17.355
$Age_{i,t}{}^{a}$	1189.504	938.440	1562.17	1011.333	1295.567	978.519
$Discountprice_{i,t}{}^{a}$	87.803	354.024	59.625	146.931	65.750	177.924
$Discount_{i,t}{}^{a}$	33.476	181.685	24.916	98.133	30.723	117.260
$Freeship_{i,t}{}^{a}$	.453	.498	.418	.493	.454	.498

Notes: t=2,…,14.

Table 3. Estimation Results of the impact of CNETD WOM and Free Sampling on the Feedback Mechanism between Volume of Amazon User Reviews and Amazon Sales

		Antivirus Software		Windows Media Player		Download Manager	
		M	95% C.I.	M	95% C.I.	M	95% C. I.
AmazonWOM equation							
$Lnrank_{i,t-1}^{a}$ (α_1)		**-26.160**	(-26.770, -25.510)	**-23.650**	(-24.17, -23.16)	**-31.890**	(-32.84, -30.88)
$Dummyuser_{i,t-1}^{a}$ (α_2)		**9.956**	(4.949, 14.680)	**15.420**	(11.69, 19.13)	10.110	(.0312, 19.430)
$Urating_{i,t-1}^{a}$ (α_3)		**-3.072**	(-4.366, -1.681)	**-9.117**	(-10.14, -8.106)	**-6.588**	(-9.014, -4.090)
AmazonSales equation							
$Uservolume_{i,t-1}^{a}$ (β_1)		**-.031**	(-.032, -.031)	**-.028**	(-.029, -.027)	**-.025**	(-.026, -.024)
$Dummyuser_{i,t-1}^{a}$ (β_2)		-.108	(-.264, .042)	**-.856**	(-1.019, -.708)	**-1.034**	(-1.397, -.658)
$UratingR_{i,t-1}^{a}$ (β_3)		**-.124**	(-.167, -.079)	**-.318**	(-.350, -.286)	**-.182**	(-.304, -.060)
$UratingRsq_{i,t-1}^{a}$ (β_4)		-.003	(-.023, .017)	**-.057**	(-.080, -.053)	**-.065**	(-.116, -.013)
$Userdispersion_{i,t-1}^{a}$ (β_5)		**-.113**	(-.173, -.052)	**-.404**	(-.467, -.343)	**-.182**	(-.250, -.112)
Endogeneity ($\sum_{\varepsilon\delta}^{a}$)		**.932**	(.928, .935)	**.826**	(.818, .834)	**.900**	(.893, .907)
Hierarchical CNETD moderation equations							
$Dummyuser_{j,t-1}^{c}$	**Eq. 4** (γ_1)	**-.878**	(-1.349, -.448)	**-.487**	(-1.025, -.068)	**-1.711**	(-3.390, -.061)
	Eq. 5 (λ_1)	-.002	(-.009, .004)	**.020**	(.005, .035)	.007	(-.002, .016)
$Dummypro_{j,t-1}^{c}$	**Eq. 4** (γ_2)	-.389	(-1.049, .227)	-.504	(-1.259, .204)	**-4.309**	(-7.452, -1.323)
	Eq. 5 (λ_2)	-.0001	(-.009, .009)	-.006	(-.028, .017)	-.011	(-.026, .004)
$Logweekdown_{j,t-1}^{c}$	**Eq. 4** (γ_3)	.070	(-.014,.146)	**.196**	(.096, .298)	**.620**	(.174, 1.087)
	Eq. 5 (λ_3)	.0003	(-.001, .001)	.001	(-.002, .004)	.001	(.001, .003)

Notes: The boldface indicates that the 95% credible interval (C.I.) does not include zero and thus the parameter is significant. Results of other control variables are not reported; data are available upon request.