THE IMPACT OF THIRD-PARTY INFORMATION ON THE DYNAMICS OF ONLINE WORD-OF-MOUTH AND RETAIL SALES

Completed Research Paper

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Abstract

Consumers have been widely searching information on third-party and retail websites before making product choices, yet receiving limited systematic investigation of how consumers process third-party information and retailer-hosted (internal) word-of-mouth (WOM) and its consequences on retail sales. In this research, we examine the impact of third party information on the dynamics of internal WOM and retail sales by analyzing a simultaneous equation system in a Bayesian hierarchical framework in online software market. We find that third-party information moderates the positive feedback mechanism between internal WOM and retail sales. Receiving third-party reviews positively interact with retail sales to increase volume of internal WOM, thus leading to more sales; whereas consumer adoption of free-trial services negatively moderates the impact of retail sales on internal WOM, which may potentially have a negative impact on future sales indirectly. The findings imply that third-party information interact with retail website information in influencing consumers' product choices.

Keywords: Word-of-mouth, third-party information, consumer information search, simultaneous equation, Bayesian hierarchical framework, software market, Amazon

Introduction

Electronic marketplaces have grown unprecedentedly popular by providing consumers abundant product choices, enormous product information and the convenience of shopping without the limitations on time and location. According to U.S. Census Bureau, the total e-commerce sales for 2010 were estimated at $165.4 billion, an increase of 14.8 percent from 2009. Online retail website and third-party infomediary become two most common types of e-commerce outlets with different service concentrations. Among various types of information these two outlets may carry, online Word-of-Mouth (WOM) functions as one of the major sources for product information that helps consumers signal product quality and reduce their decision risk without physical trials. Managers have widely embraced and facilitated online WOM as a complementary strategy for advertising to enhance retail sales. Promotional chat, buzz marketing and review community on either retail or third-party websites all reflect this strategy. Numerous studies have also provided convincing evidence for this strategy. Both retailer-hosted (internal) WOM and third-party-hosted (external) WOM information have been shown to influence retail sales in various contexts (Chevalier and Mayzlin 2006; Dhanasobhon et al. 2007; Duan et al. 2008; Forman et al. 2008; Godes and Mayzlin 2004; Liu 2006). Recently online retailers even start to invest in the content of third-party websites in addition to their own content internally (Jupiter Research 2005). This emerging practice receives encouraging voice from some scholars who argue that the external WOM is more influential on retail sales than the internal WOM (Gu et al. 2011; Senecal and Nantel 2004).

Nevertheless, both anecdotal evidence as well as some economic and marketing literature cast doubt on the expected benefits from the provision of third-party information on retail sales. Third-party websites not only provide WOM information as most retail websites do but also offer free-trial experiences, aggregate product price information, provide comparison report of product characteristics, and etc. Various types of information available on third-party websites may have different impact on retail sales. The nature of the information offered by third-party websites is critical to determine whether the firms benefit from the existence of third-party infomediary (Shaffer and Zettelmeyer 2002). As such, it requires systematic and rigorous investigations to examine whether the provision of various types of third-party information all benefits online retail sales.

In addition, some third-party information may even hurt online retail sales from the perspective of channel management. Kuruzovich et al. (2008) pointed out that consumer purchase decision through referral intermediary, as one specific example of third-party infomediary, does not fit within the category of purchase through online retail channel in terms of channel management. Third-party infomediary usually generates profits from advertising and referral services to manufacturers and retailers, being different from directly selling products on retail websites. In theory, this inherent difference in the goals of two channels would inevitably result in conflicts over customers and internal manufacturers' resources (Webb 2002). Although having not been fully investigated in prior studies, third-party websites may act as a distinct channel from retail websites and result in new channel conflicts in the e-commerce age. Online retail sales could therefore suffer from the downsides of the conflicts of online retail channel with the introduction of third-party channel, similar as its conflicts with offline retail channel. For example, the usage of online search engine, as another example of third-party infomediary, has been shown to reduce consumers' purchases on retail websites (Waldfogel and Chen 2006).

A better understanding of the differential impact from various types of third-party information on online retail sales, considering the influence of internal WOM, could offer important managerial implications. Managers need guidance to determine whether and to what extent their products should engage in online third-party channel; they also need to adjust and vary their marketing strategy from information on third-party websites. Due to the lack of systematic research, there is an essential need to bring empirical evidence in academic research to bear on these issues.

In this paper, we aim to investigate this under-explored area by addressing the research question: whether and how the various types of third-party information influence the dynamics between internal WOM and online retail sales. Previous research suggest that consumers' participations in online WOM activities and purchase behaviors on retail websites could be explained by a positive feedback mechanism (Duan et al. 2008; Godes and Mayzlin 2004).The online internal WOM activities may enhance consumer awareness of the relevant products, leading to more sales; while the more past sales indicate a larger user base, leading to more user-generated WOM activities (Duan et al. 2008). Meanwhile, the literature regarding online information search suggest that consumers use third-party websites before their information search and purchases on retail websites (ComScore 2007; Gu et al. 2011; Row 2006). Therefore, the provision of third-party information may moderate the internal feedback mechanism between WOM and sales on retail websites. Specifically, we propose that consumers' pre-purchase information search on third-party websites influences consumers' decision-making on retail websites via its interaction with internal WOM; third-party information also influences consumers' participations in internal WOM activities via its interaction with past retail sales.

To investigate the proposed moderation effect, we collected a panel data of third-party information from CNETD (CNET www.download.com) software programs along with the sales ranks and user review information of the matched Amazon (www.amazon.com) products over 14 weeks. Our empirical model is composed of a simultaneous equation system to model the feedback mechanism between internal WOM and retail sales, along with two hierarchical moderation equations to model the moderation effect of third-party information. The estimation results through MCMC (Markov chain Monte Carlo) method provide evidence that external WOM and consumer adoption of free-trial services offered by third-party websites moderate the positive feedback mechanism between internal WOM and retail sales. Receiving third-party reviews on CNETD enhance the positive impact of the past sales of its matched Amazon product on its volume of Amazon user reviews, leading to more sales afterwards; whereas a larger number of software downloads, indicating the corresponding product's success on CNETD, reduces the volume of Amazon user reviews of its matched Amazon products through the interaction with past sales, which may potentially hurt future sales. To our best knowledge, this paper is the first to examine the detailed mechanism under which third-party information influence the dynamics of online WOM and retail sales. .

The rest of paper proceeds as follows. The literature is reviewed in the next section, which is followed by the conceptual framework. We then describe the data and analyze the empirical model. In the last section, we discuss the results and implications, and conclude the paper by addressing the limitations and identifying areas for future research.

Literature Review

Our work is mostly related to prior research examining the online WOM effect. Most work study the impact of online WOM information generated by a single reviewer identity (ordinary consumers, professionals or sellers) on online consumer decision-making. Many studies have emphasized on the influence of professional reviews on consumer product choices (Basuroy et al. 2003; Boatwright et al. 2007; Reinstein and Snyder 2005). Extensive recent research, however, have agreed on the significant impact of user-generated WOM information on consumers' product choices (Chevalier and Mayzlin 2006; Dhanasobhon et al. 2007; Duan et al. 2008; Forman et al. 2008; Godes and Mayzlin 2004; Liu 2006). Among them, very limited studies consider the differential impact of WOM information from multiple reviewer identities (Amblee and Bui 2007; Bickart and Schindler 2001; Senecal and Nantel 2004; Zhou and Duan 2010).

Recently, there has been growing attention on the differential impact of online WOM information provided by different types of e-commerce outlets, i.e., third-party infomediary and retail website (Gu et al. 2011; Senecal and Nantel 2004). Senecal and Nantel (2004) studied one special type of online WOM information —product recommendations. They found that product recommendations on third-party websites are more influential on consumers' online choices than product recommendation on retailer-related websites. Gu et al. (2011) conducted a similar comparison of user-generated WOM in the context of high-involvement products. They found that external WOM has significant impact on online retail sales of digital camera, while the impact of internal WOM is very limited.

The common underlying assumption of the aforementioned two studies is that external WOM and internal WOM both directly and independently influence retail sales. However, prior studies have shown that their relationships with retail sales could be more complicated. In terms of internal WOM, prior studies suggest that there may exist a feedback mechanism between WOM and retail sales. Godes and Mayzlin (2004) pointed out that online WOM is also an outcome of retail sales in addition to its function of influencing sales. It is further supported by a recent study (Duan et al. 2008) showing that movie revenues positively influence volume of online WOM, which in turn influence box office performance.

Online WOM is endogeneous in nature, and its relationship with retail sales is intricate. In particular, consumer behavior with regard to internal WOM on retail websites can be decomposed of two major processes. One is consumer purchase decision with the help of internal WOM, and the other is consumer post-purchase contribution to internal WOM. The former reflects the sales driving force from internal WOM, which has been widely discussed as mentioned beforehand. The latter reveals the generation process of internal WOM; that is internal WOM is positively related with user base, which could be approximately indicated by retail sales. As a result, the process of consumers' participations in internal WOM activities and their decision-making on retail websites has been suggested to be characterized by a positive feedback mechanism between internal WOM and retail sales.

In terms of external WOM, the literatures on online consumer information-search behavior imply that third-party information including external WOM could moderate consumer behavior on retail websites. Consumers are believed to navigate both inter-site and intra-site to search for information and consummate their purchase process (Hodkinson and Kiel 2003). A few studies have made logical arguments supported by empirical evidence that consumers often look into third-party websites before their information search on retail websites (Gu et al. 2011; Row 2006). This implies that the information gathered by consumers from third-party websites may influence consumers' further reactions to information on retail websites.

Therefore, it is expected that the provision of third-party information may moderate the positive feedback mechanism between internal WOM and consumers' final purchase decisions. First, consumers' reliance on the internal WOM on retail websites could be moderated by third-party information. Some scholars have identified the moderation effect of various contextual variables on online WOM effect in different contexts (Cheema and Papatla 2010; Zhou and Duan 2009; Zhu and Zhang 2010). Zhu and Zhang (2010) applied the classic psychological choice models proposed by Hansen (1976) to the e-commerce setting and argued that consumers' reliance on user reviews is affected by contextual variables. Contextual variables are conventionally defined to describe the context where brain processes occur and consumers make their behavioral responses subsequently, such as store size, promotion event, product category, and so forth (Hansen 1976). Zhu and Zhang (2010) and Cheema and Papatla (2010) identified product characteristic and product category as the contextual variables for online WOM effect respectively. As consumers are expected to look into third-party websites first, third-party information also falls into the territory of contextual variables. Hence, the internal WOM effect, as one component of the feedback mechanism between internal WOM and retail sales, is very likely moderated by third-party information.

Second, consumers' motivations to participate in internal WOM activities could be moderated by third-party information. Consumer posting behavior has been shown by prior studies to be subject to social influences, e.g., previously posted reviews (Godes and Silva 2009; Li and Hitt 2008; Moe and Trusov 2011; Schlosser 2005). Schlosser (2005) pointed out that consumers strive to differentiate their reviews. This is consistent with studies on consumers' willingness to share their experiences online (Hennig-Thurau et al. 2004). Consumers participate in online WOM activities partly to enhance their own self-worth. Therefore, consumers could increase their perceived likelihood to enhance their own self-worth either by differentiating their reviews from others or by choosing to write reviews on eye-catching products. Since consumers often refer to third-party websites before they look into internal WOM, they very likely formalize a candidate list for products to be considered on retail websites based on third-party information(Hodkinson and Kiel 2003). In other words, third-party information influences consumers' choices of products on retail websites to look into, which influences the importance of reviews of those products in their candidate list. Therefore, consumers' willingness to write reviews on those products could be different from other products.

Conceptual Framework

Before presenting our data and empirical analysis, in this section, we discuss our conceptual framework underlying this study illustrated by Figure 1. The third-party information including third-party professional reviews, third-party user-generated reviews, and consumer adoption of third-party free-trial service are expected to influence the feedback mechanism between internal WOM and online retail sales.

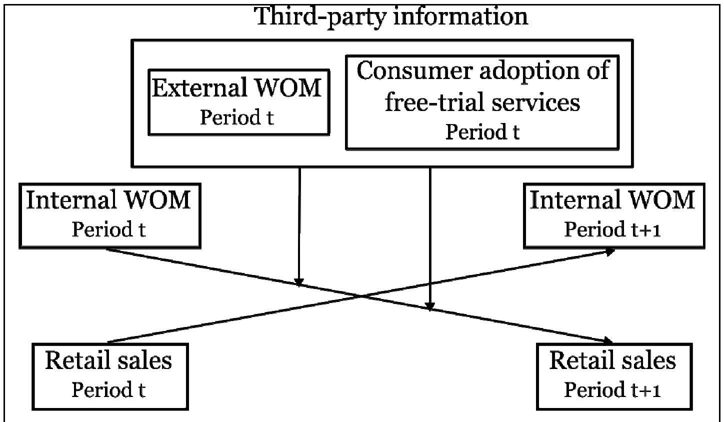

Figure 1. Conceptual Framework

A key metric of internal WOM is the volume of user-generated WOM activities, which is shown to have the most explanatory power for consumer choices compared to other metrics (Duan et al. 2008; Liu 2006). The volume of internal WOM influences consumer awareness as a cognitive consequence, which influences consumer choices at the end (Liu 2006). The more internal WOM activities a product receives, the more likely consumers may get informed of it, thus leading to more consumer choices (Godes and Mayzlin 2004). Besides influencing sales, the volume of online user reviews is found to be an outcome of retail sales (Duan et al. 2008; Godes and Mayzlin 2004). The underlying rational is that greater sales indicate a larger user base, thus leading to more user feedback.

In this paper, we consider the third-party information including mainly two types: external WOM information and consumer adoption of free-trial services. Third-party websites often provide independent reviews as expert opinions on selected products, in addition to the user-generated contents. Compared to user-generated reviews, professional reviews may provide more authoritative judgments by precluding personal biases to some degree (Amblee and Bui 2007). Hence, we examine external WOM information generated by both two distinct reviewer identities, namely external professional reviews and external user-generated reviews. We also include consumer adoption of free-trial services to represent product performance on third-party websites. Nowadays, beyond providing external WOM information, many vendors start to offer sampling and free-trial mechanisms on third party websites, such as free software downloading on CNETD and free music listening on Pandora. Consumers are facilitated with those free-trial services as the direct experience to learn about products while the online WOM serves as indirect exposure to others' experience (Kulviwat et al. 2008). Therefore, it is also important to study whether the most popular product on third-party websites would continue its success on retail websites as well as whether the direct experience and indirect experience differ in their ways to interact with the feedback mechanism between internal WOM and online retail sales.

The moderation effect of third-party information on the feedback mechanism between internal WOM and retail sales is expected to be two-way. First, external WOM and consumer adoption of free-trial services are anticipated to moderate the impact of volume of internal WOM on retail sales. Third-party information influences consumers' initial evaluations of a certain product before they proceed to assess product quality on retail websites. Based on these initial evaluations, they could update their pre-purchase evaluations by referring to the online WOM information available on retail websites. Therefore, for a given product, all else being equal, distinct situation of external WOM and consumer adoption of free-trial services on third-party websites would lead to differential impact of internal WOM of the relevant product on retail websites.

Second, external WOM and consumer adoption of free-trial services are expected to moderate the impact of past retail sales on volume of internal WOM. We did not focus on the moderation effect of third-party information on the valence of internal WOM. Instead, we examine the moderation effect on consumers' motivations to engage in internal WOM activities after consumptions. The expectation of such moderation effect implies that for a given level of past retail sales, consumers could be more or less willing to share their experiences of a product on retail websites given their information search process and product trial experience on third party websites.

Our subsequent modeling aims to reveal and quantify the detailed aspects of these moderation effects on the feedback mechanism between volume of internal WOM and retail sales. We develop a model that both captures the endogeneity of volume of internal WOM and robustly measures the moderation effect of third-party information. We present our model after discussing research context and data in the next section.

Data

Research Context

We conduct our empirical analysis using a panel data over 14 weeks in online software market. Software market is extraordinarily competitive. Both popular and niche software programs have increased tremendously over years (Zhou and Duan 2009). In 2013, the global software market is forecasted to have a value of $457 billion, an increase of 50.5% since 2008, in which the U.S. accounts for 42.6%.[1] In addition, software programs, as one type of experience goods, generally result in consumers' difficulties to observe and assess product quality before their consumptions. Hence, abundant product choices and the nature of experience goods require consumers to extensively search for product information before making purchase decisions.

We collect retail sales rank and internal WOM data from Amazon. We choose Amazon to represent the retail website that consumers may finally purchase software programs and share their feedback as Amazon is widely adopted in e-commerce research for examining online market outcome. Amazon also implements a five-star rating system to allow consumers share their experience and summarizes user reviews for each product by an overall average rating, total number of user reviews and number of user reviews for each rating scale.

We collect third-party information from CNETD including external WOM and online software downloading. We assume that consumers may very likely resort to CNETD as their choice of third-party websites for trying out free trials of software programs and looking for third-party WOM information to signal product quality, since CNETD is a leading and representative third-party website for software download. It is a library of over 80,000 free or free-to-try software programs for four different platforms including Windows, Mac, mobile device and webware. For each platform on CNETD, there are more than 20 groups of software programs with approximately 6~20 categories in each group. CNETD lists detailed product descriptions as well as weekly and cumulative download counts for each software program. Similar to Amazon, on CNETD, users can also post their reviews by detailed comments and an overall rating on a scale of one to five, with one being the worst and five the best. CNETD also provides editorial reviews for selected software programs in a similar manner by a five-star rating system (usually popular products).

We collect data weekly on all products of three categories listed on CNETD and matched products sold by Amazon for the period November 2010 through February 2011. These three categories are: Antivirus Software, Digital Media Player and Download Manager, which include categories with different application purposes. We extract the following information on every software program listed in each category on CNETD at the beginning of every week: software name, last week downloads, whether the product receives user reviews, average user rating, total number of user reviews, whether the product receives CNETD editor review and the CNETD editor rating. Meanwhile we also collect data on matched Amazon products based on the "relevance" search criteria within the same category. We conduct the following matching process. For each software program collected on CNETD, we search for the exact software name within the department of software on Amazon and collect the first 60 most relevant Amazon products from the search results. Hence, one CNET product might be matched up to 60 Amazon software programs, yet each collected Amazon product is matched to only one CNET product with a

[1] Software: Global Industry Guide (2009).

relevance order. In particular, on Amazon, we collect software name, relevance order with CENTD product, rank, whether receiving user reviews, average user rating, total number of user reviews, number of user reviews for each rating scale, first available date, price, discount on price, and eligibility for free-shipping service. Since every category represents a unique group of software with similar application purposes, we define each category as a single market.

Measures

We use Amazon sales rank as the proxy for Amazon sales. Extant studies have identified a power law relationship between sales and sales rank in various contexts (Brynjolfsson et al. 2003; Ghose and Sundrararajan 2005; Gu et al. 2011; Smith and Telang 2008). Ghose and Sundrararajan (2005) conducted an experiment to apply the power law to Amazon software sales rank to estimate actual sales. Following these studies, we take a similar approach and use Amazon sales rank with a log transformation ($Lnank_{i,t}^{a}$) to approximately measure the log values of actual sales, given the negative linear relationship between them.

Table 1. Description of Key Variables	
CNETD (upper *c* denotes CNETD)	
$Dummyuser_{j,t}^{c}$	A dummy variable measures if software *j* receives any user reviews by week *t*
$Dummypro_{j,t}^{c}$	A dummy variable measures if software *j* receives CNET editor review by week *t*
$Weekdownload_{j,t}^{c}$	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*
$Dummyuser_{i,t}^{a}$	A dummy variable measures if software *i* receives any user reviews by week *t*
$Urating_{i,t}^{a}$	Average user rating of software *i* by week *t*
$Relevance_{i,t}^{a}$	The relevance order of software *i* with its matched CNETD product 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*
$Freeship_{i,t}^{a}$	A dummy variable measures if software *i* is eligible for free shipping at week *t*

Following Godes and Mayzlin (2004) and Liu (2006), we use one-week lagged independent variables to model the feedback mechanism between Amazon WOM and Amazon sales. This technique would help better reflect the process of consumers' participations in WOM activities and their decision-making. The time lag also helps to reveal the causality relationship. Therefore we only keep the observations whose Amazon software programs have appeared during two consecutive weeks, which leads to our final sample of 13 weeks of panel data set. Table 1 provides the description of key variables, and Table 2 presents the summary statistics of the variables. The summary statistics shows that less than 20% CNETD products have received CNETD editor reviews in all categories.

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)	
Weekly number of CNETD products	70.154	1.951	122	3.493	40.308	2.097
$Dummyuser_{j,t-1}{}^{c}$	0.735	0.442	0.531	0.499	0.632	0.483
$Dummypro_{j,t-1}{}^{c}$	0.185	0.389	0.138	0.345	0.141	0.349
$Weekdownload_{j,t-1}{}^{c}$	5717.565	54381.82	883.493	4784.84	2175.33	16729.02
Weekly number 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
$Dummyuser_{i,t-1}{}^{a}$	0.689	0.463	0.676	0.468	0.808	0.394
$Urating_{i,t-1}{}^{a}$	2.199	1.7126	2.217	1.747	2.776	1.559
$Relevance_{i,t-1}{}^{a}$	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
$Freeship_{i,t}{}^{a}$	0.453	0.498	0.418	0.493	0.454	0.498
Notes: t=2,…,14.						

Empirical Analysis

Empirical Model

We build our model in a Bayesian hierarchical framework as a robust approach to analyze the moderation effect. The whole model system is composed of a simultaneous equation system along with two hierarchical moderation equations as presented below. We simultaneously model the feedback mechanism between volume of Amazon user reviews and Amazon retail sales by two interdependent equations. The first equation (the AmazonWOM equation) in this system includes $Uservolume_{i,t}{}^{a}$ as a dependent variable and the second equation (the AmazonSales equation) includes $Lnrank_{i,t}{}^{a}$ as a dependent variable. The adoption of simultaneous modeling approach allows errors of these two equations to be contemporaneously correlated. Since the volume of user reviews has been demonstrated to be endogenous (Duan et al. 2008), it is expected that omitted factors may exist in both two equations and simultaneously influence both volume of Amazon user reviews and Amazon retail sales. By estimation results of this simultaneous equation system, we would be able to evaluate the impact of past retail sales on volume of internal user reviews via the coefficient on $Lnrank_{i,t-1}{}^{a}$ (α_1) and the impact of volume of internal user reviews on online retail sales via the coefficient on $Uservolume_{i,t-1}{}^{a}$ (β_1), when the moderation effect from third-party information is not considered.

AmazonWOM equation

$$Uservolume_{i,t}^{a} = \alpha_0 + \alpha_1 * Lnrank_{i,t-1}^{a} + \alpha_{j,t-1}^{c} * Lnrank_{i,t-1}^{a} * (1/\mathrm{Re}levance_{i,t-1}^{a}) + \alpha_2 * Dummyuser_{i,t-1}^{a}$$
$$+\alpha_3 * Dummyuser_{i,t-1}^{a} * Urating_{i,t-1}^{a} + \alpha_4 * Age_{i,t}^{a} + \alpha_5 * Agesq_{i,t}^{a} + \varepsilon_{i,t}^{a} \quad (1)$$

AmazonSales equation

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

CNETD hierarchical moderation equations

$$\alpha_{j,t-1}^{c} = \gamma_1 * Dummyuser_{j,t-1}^{c} + \gamma_2 * Dummypro_{j,t-1}^{c} + \gamma_3 * Logweekdown_{j,t-1}^{c} + \omega_{j,t-1}^{c} \quad (3)$$

$$\beta_{j,t-1}^{c} = \lambda_1 * Dummyuser_{j,t-1}^{c} + \lambda_2 * Dummypro_{j,t-1}^{c} + \lambda_3 * Logweekdown_{j,t-1}^{c} + \upsilon_{j,t-1}^{c} \quad (4)$$

$$\begin{bmatrix} \varepsilon_{i,t}^{a} \\ \delta_{i,t}^{a} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sum_{\varepsilon\varepsilon}^{a} & \sum_{\varepsilon\delta}^{a} \\ \sum_{\delta\varepsilon}^{a} & \sum_{\delta\delta}^{a} \end{bmatrix} \right), \ \omega_{j,t-1}^{c} \sim N(0, \textstyle\sum_{\omega\omega}^{c}), \ \upsilon_{j,t-1}^{c} \sim N(0, \textstyle\sum_{\upsilon\upsilon}^{c})$$

In addition, we conduct a pair of two hierarchical moderation equations (equations 3 & 4) to model the moderation effects of CNETD WOM and weekly download on the feedback mechanism. The hierarchical structure is shown as a more robust approach to model the moderation effect than the conventional way of using interaction term (Zhou and Duan 2010). Hence, we build up hierarchical structures on the coefficients on $Lnank_{i,t-1}^{a}$ $*(1/Relevance_{i,t-1}^{a})$ in the AmazonWOM equation and $Uservolume_{i,t-1}^{a}$ $*(1/Relevance_{i,t-1}^{a})$ in the AmazonSales equation respectively. As described beforehand in data collection, each i^{th} Amazon product is matched to a j^{th} CNETD product with a relevance order ($Relevance_{i,t-1}^{a}$). Since the i^{th} Amazon product might not be exactly the same as j^{th} CNETD product, we assume that the moderation effect from the information of j^{th} CNETD product on i^{th} Amazon product should be more significant when these two products are more relevant. Note that the closer relevance leads to a smaller value of $Relevance_{i,t-1}^{a}$. As a result, we include the inversed relevance order $(1/Relevance_{i,t-1}^{a})$ to shape the moderation effect.

We allow the coefficients on $Lnrank_{i,t-1}^{a}$ $*(1/Relevance_{i,t-1}^{a})$ ($\alpha_{j,t-1}^{c}$) and $Uservolume_{i,t-1}^{a}$ $*(1/Relevance_{i,t-1}^{a})$ ($\beta_{j,t-1}^{c}$) to be heterogeneous over the j^{th} CNETD product every week, leading to two hierarchical moderation equations. The two error terms in these two equations ω and υ could control for other omitted CNETD information and information from other third-party websites that consumers may search on besides CNETD. This separates and controls for the moderation effect of third-party information provided by other websites and thus adds to the robustness of our estimations. If adopting the conventional approach of using interaction term, the moderation effects of these omitted third-party information would be retained in the error terms of AmazonWOM and AmazonSales equations. These moderation effects would then correlated with $Lnrank_{i,t-1}^{a}$ in the AmazonWOM euation and $Uservolume_{i,t-1}^{a}$ in the AmazonSales equation respectively, thus resulting in the endogeneity issue. Instead, the hierarchical framework helps separate those noises from estimating the simultaneous equation system and provides unbiased estimates for the feedback mechanism between Amazon WOM and sales. The WOM information of j^{th} CNETD product is indicated by two dummy variables: whether the j^{th} CNETD product has received any CNETD user reviews ($Dummyuser_{j,t-1}^{c}$) and whether this product has received any CNETD editor review ($Dummypro_{j,t-1}^{c}$). Consumer adoption of free-trail services of j^{th} CNETD product is measured by its number of weekly downloads. We apply a log transformation on weekly downloads ($Logweekdown_{j,t-1}^{c}$) in order to convert the value to a comparable magnitude to other variables. Therefore, by estimating the whole model system, we would be able to show the moderation effect of third-party information on the feedback mechanism between volume of internal WOM and online retail sales by monitoring two pairs of coefficients: three coefficients in equation 3 (γ_1, γ_2, γ_3) and three coefficients in equation 4 (λ_1, λ_2, λ_3).

Following previous studies, we also include various other variables in the simultaneous equation system. Prior studies have shown that valence of user reviews significantly influences consumer choices (Chevalier and Mayzlin 2006; Moon et al. 2010; Zhou and Duan 2009). Hence, for the AmazonSales equation, we include the valence of Amazon user-generated WOM. Chevalier and Mayzlin (2006) found that 1-star user reviews hurt sales more than 5-star reviews benefit sales. As a result, we follow the technique used by

Zhou and Duan (2009) in their study to differentiate the impacts of user reviews with different rating levels on retail sales. We apply a minor linear transformation on $Urating_{i,t-1}^{a}$ and use ($Urating_{i,t-1}^{a} -3$) instead, as 3 is the middle point of Amazon rating range. For parsimony, we name the new variable $Uratingr_{i,t-1}^{a}$ and include its quadratic term, denoted by $Uratingsq_{i,t-1}^{a}$ to assess the nonlinear impact of user reviews of different rating levels. Moreover, Godes and Mayzlin (2004) applied the "entropy" of consumer conversations to measure the dispersion of WOM. They have shown that dispersion of WOM is an informative metric of online WOM and is better measured by entropy than by variance. We, thus, also include another metric of Amazon WOM: the dispersion of Amazon user reviews $Userdispersion_{i,t-1}^{a}$, which is calculated from the number for each rating scale for i^{th} product. In addition, price effects are controlled by the discount price $Discountprice_{i,t-1}^{a}$ and the value of offered discount $Discountp_{i,t-1}^{a}$. A dummy variable $Freeship_{i,t-1}^{a}$ is used to control for the difference in availability of free-shipping service among the collected software programs. We also use product age $Age_{i,t-1}^{a}$ and the quadratic term of product age $Agesq_{i,t-1}^{a}$ to control for product diffusion (Duan et al. 2009). $Age_{i,t-1}^{a}$ and $Agesq_{i,t-1}^{a}$ are also included in the AmazonWOM equation. We also include information about valence of Amazon user reviews ($Dummyuser_{i,t-1}^{a}$, $Urating_{i,t-1}^{a}$) in the AmazonWOM equation as suggested by Duan et al. (2008) in their study to examine the dynamic feedback mechanism between online WOM and offline retail sales.

Results

We implement our empirical model system in a Bayesian framework and estimate it using MCMC method for each category mainly for three reasons. First, there have always been some arguments among frequentists regarding the appropriate sample size for utilizing the asymptotic inference. Bayesian framework naturally gets rid of this asymptotic assumption and provides a neat approach to avoid this issue. Moreover, MCMC method is flexible and robust to estimate any functions of parameters without the "plug-in" method due to its nature of simulation process. More importantly, Bayesian framework is a convenient setting for some models including hierarchical model, which would otherwise be computationally infeasible in frequency framework (Kass et al. 1998). Specifically, we use a burn-in of 15,000 draws and thin the 15,000 target draws by 1 in every 10 draws to characterize the posterior distributions of parameters. The convergence is monitored by visually checking the history plots and inspecting Gelman-Rubin diagnostic (BGR), which confirms the validity of estimate results. We specify very vague priors for all unknown parameters. We assume normal $N(0,10^{3})$ prior distributions for all regression coefficients, inverse gamma $IG(10^{-3},10^{-3})$ prior distributions for the variance parameters of two independent errors (ω^{c} and υ^{c}), and inverse wishart IWR($\begin{matrix} 1 & 0 \\ 0 & 1 \end{matrix}$,2) prior distribution for the variance matrix of two correlated errors of the simultaneous equation system. Table 3 shows the estimation results in each category of the posterior means and standard deviations.

Table 3. Estimation Results of the Moderation Effect of CNETD Information on the Feedback Mechanism between Volume of Amazon Reviews and Amazon Sales

		M	SD	M	SD	M	SD
		Antivirus Software		Windows Media Player		Download Manager	
AmazonWOM equation							
Lnrank$_{i,t-1}^{a}$ (α_1)		**-26.160**	0.319	**-23.650**	0.260	**-31.890**	0.497
Dummyuser$_{i,t-1}^{a}$ (α_2)		**9.956**	2.484	**15.420**	1.909	10.110	4.940
Urating$_{i,t-1}^{a}$ (α_3)		**-3.072**	0.674	**-9.117**	0.517	**-6.588**	1.270
AmazonSales equation							
Uservolume$_{i,t-1}^{a}$ (β_1)		**-0.031**	0.0004	**-0.028**	0.0004	**-0.025**	0.0004
Dummyuser$_{i,t-1}^{a}$ (β_2)		-0.108	0.077	**-0.856**	0.082	**-1.034**	0.184
Uratingr$_{i,t-1}^{a}$ (β_3)		**-0.124**	0.022	**-0.318**	0.016	**-0.182**	0.035
Uratingrsq$_{i,t-1}^{a}$ (β_4)		-0.003	0.010	**-0.057**	0.012	**-0.06**	0.025
Userdispersion$_{i,t-1}^{a}$ (β_5)		**-0.113**	0.031	**-0.404**	0.032	**-0.182**	0.062
Correlation between errors		**0.932**	0.002	**0.826**	0.004	**0.900**	0.004
Hierarchical moderation equations							
Dummyuser$_{j,t-1}^{c}$	**Eq. 3** (γ_1)	**-0.878**	0.235	**-0.487**	0.277	**-1.711**	0.850
	Eq. 4 (λ_1)	-0.002	0.003	0.020	0.008	0.007	0.004
Dummypro$_{j,t-1}^{c}$	**Eq. 3** (γ_2)	-0.389	0.328	-0.504	0.363	**-4.309**	1.556
	Eq. 4 (λ_2)	-0.0001	0.005	-0.006	0.012	-0.011	0.008
Logweekdown$_{j,t-1}^{c}$	**Eq. 3** (γ_3)	0.070	0.041	**0.196**	0.052	**0.620**	0.233
	Eq. 4 (λ_3)	0.0003	0.001	0.001	0.002	0.001	0.001
DIC		102219.000		132088.000		56602.800	
Notes: boldface type indicates the significance of estimators, namely the 95% posterior credible interval does not cover zero. Results of other control variables are not reported due to page limitation, which are available upon request.							

We first examine the feedback mechanism between volume of Amazon reviews and Amazon sales when the moderation effect of CNETD information is not considered. For the AmazonWOM equation, the impact of Amazon sales on its volume of user reviews is significantly positive. The coefficient on *Lnank*$_{i,t-1}^{a}$ (α_1) is negative in all three categories, which actually indicates a positive relationship, given the negative linear relationship between the log values of rank and log values of sales. For the AmazonSales equation, similarly the impact of volume of Amazon reviews on its sales is shown to be significantly positive indicated by the negative coefficient on *Uservolume*$_{i,t-1}^{a}$ (β_1) in each category. Therefore, if third-party websites were not available for consumers to resort to or their moderation effects were omitted, we find a positive feedback mechanism between internal WOM and online retail sales, which is consistent with prior findings in the study conducted by Duan et al. (2008) using movie data.

We now proceed to discuss the contingent relationship between third-party information and the positive feedback mechanism between internal WOM and retail sales. We find that all coefficients ($\lambda_1, \lambda_2, \lambda_3$) on the second hierarchical moderation equation are insignificant. This seems to imply that neither external WOM nor consumer adoption of free-trial services on third-party websites moderates the impact of internal WOM on retail sales. Consumers are simply attracted to consider the product by its large volume of online user reviews, which has nothing to do with their adoptions of its free trial and their information search of external WOM. On the other hand, the results of the first hierarchical moderation equation show that third-party information does moderate the positive impact of retail sales on internal WOM. The coefficient on $Dummyuser_{j,t-1}^{c}$ (γ_1) is significantly negative, which adds to the magnitude of the negative coefficient α_1 in the AmazonWOM equation of the simultaneous equation system. Hence, receiving external user reviews positively moderates the impact of Amazon sales on volume of Amazon reviews in all categories as we expected. In category of Download Manager, we find that receiving external professional reviews also positively moderates the impact of Amazon sales on volume of Amazon reviews, indicated by the negative coefficient on $Dummypro_{j,t-1}^{c}$ (γ_2). Yet γ_2 turns insignificant in both the other two categories. We believe this is most likely due to the small sample size, given that only a very small portion of CNETD products are offered CNETD editor reviews. For example, in those two categories of Antivirus Software and Digital Media Player, only 18.5% and 13.8% products received CNETD editor reviews respectively as indicated by Table 2. As a result, the variation for the dummy variable $Dummypro_{j,t-1}^{c}$ is expected to be small, which could lead to falsely reject the null hypothesis.

In contrast, consumer adoption of free-trial services on third-party websites is found to negatively moderate the impact of retail sales on internal WOM. In categories of Digital Media Player and Download Manager, the coefficient on $LogWeekdown_{j,t-1}^{c}$ (γ_3) is significantly positive, reducing the magnitude of the negative coefficient α_1 in the AmazonWOM equation. This indicates that the success of a software program on CNETD actually makes consumers hesitate to share their experiences on Amazon after their consumptions, leading to a fewer volume of Amazon reviews. The positive feedback between volume of Amazon reviews and Amazon sales further implies that this negative moderation effect could potentially indirectly result in fewer future Amazon sales.

Overall, our current results provide evidence that third-party information moderates the positive feedback mechanism between internal WOM and online retail sales. The impact of online retails sales on volume of internal WOM is conditional on external WOM and consumer adoption of free-trial services offered by third-party websites, whereas the impact of internal WOM on retail sales does not seem to depend on third-party information. In other words, third-party information interacts with retail sales to influence volume of internal WOM, which in turn leads to changes of future retail sales.

In addition, we also notice some interesting results from our control variables. For the AmazonSales equation, dispersion of user reviews is a predictor for sales as shown by the negative coefficient on $Userdispersion_{i,t-1}^{a}$ (β_5), which echoes its informative role for sales argued by Godes and Mayzlin (2004). It further implies that larger dispersion among internal user reviews leads to more sales. The more uneven attributes of online information are perceived by consumers as higher decision quality (Lurie 2004). As such, internal user reviews for a certain product with larger dispersion carry more information and reduce consumers' risk to a larger extent, thus promoting sales. For the AmazonWOM equation, we find that more negative user review lead to more active internal WOM interactions as indicated by the negative coefficient on $Urating_{i,t}^{a}$ (α_3). This is consistent with the underlying motivations for consumers' participations in online WOM activities. Negative information gains more attention than positive information (Ahluwalia et al. 2000; Fiske 1980). Hence, consumers expect to more likely enhance their own self-worth by writing reviews on products that have received considerable negative feedback (Hennig-Thurau et al. 2004).

Finally, we check the robustness of our model for the contemporaneous correlated errors of hierarchical moderation equations. The error terms of these two equations may have omitted factors in common which simultaneously influence their dependent variables ($\alpha_{j,t-1}^{c}$, $\beta_{j,t-1}^{c}$). Due to this concern, we also estimate the whole model system by replacing the initial two hierarchical moderation models with a new SUR (Seemingly Unrelated Regression) model to allow correlated errors between Eq.3 and Eq.4.[2] The correlation between two errors is shown to be insignificant, suggesting these two equations are indeed unrelated.

[2] The detailed statistic report is available upon request.

Conclusions, Discussion and Future Research

The findings of this study have a number of implications for researchers. First, our results add to the understanding of the feedback mechanism between online WOM and retail sales. A few prior studies have provided a systematic interpretation on the sales driving role as well as the sales outcome role of online WOM (Duan et al. 2008). This study goes a step further to reveal the contingent relationship between third-party information and this feedback mechanism. Third-party information moderates the impact of retail sales on the volume of internal WOM. In other words, it influences consumers' willingness to participate in the internal WOM activities after their consumptions. This finding highlights the importance of considering the contingency for the dual causal relationship between online internal WOM and retail sales.

Second, the results also bring important extensions to previous research on consumers' information-search behavior across various websites and its consequences on market outcome. Limited research has recognized the importance to examine the interaction of consumers' information search across third-party and retail websites and its impact on retail sales. Two recent studies shed some light on this issue by comparing the impacts of internal WOM and external WOM (Gu et al. 2011; Senecal and Nantel 2004). Their underlying assumption is that online WOM from both retail and third-party websites independently and directly influence retail sales. However, we find that external WOM influences internal WOM through its interaction with retail sales. External WOM enhances consumers' motivations to share their experiences on retail websites after consumptions, indirectly promoting sales. In addition, this study also introduces another important type of third-party information: consumer adoption of free-trial services into this line of work, which is getting prevalent in practice. We find that consumer adoption of free-trial services interacts with the positive feedback mechanism between internal WOM and retail sales in an opposite approach from external WOM. In contrast to external WOM, more adoptions of free-trial services on third-party websites dampen consumers' enthusiasm for internal WOM participations, which may in turn potentially have a negative impact on future sales.

Third, this study suggests the potential conflicts between online third-party and retail channels. The emergence of e-commerce triggers widely discussion and academic investigation on the channel conflicts between online and offline retail channels (Kuruzovich et al. 2008; Tsay and Agrawal 2004; Webb 2002). The potential conflicts between these two channels have been outlined and various managerial suggestions have been proposed to facilitate online retail sales. Although a few studies have implied that third-party infomediary has distinct attributes and objectives from online retail websites (Chen et al. 2002; Iyer and Pazgal 2003), little has been known regarding the channel conflicts between third-party and retail websites. This study fills this void by recognizing third-party infomediary as a distinct channel from retail websites and thus expands the boundary of channel conflict research into a new and important territory. Our results identify that the free-trial services provided by online third-party channel may cause conflicts with online retail channel. The widely accepted free-trial services by consumers on third-party websites may weaken consumers' willingness to get involved in the WOM activities on retail websites. Although less active WOM does not reflect and transmit consumers' less satisfaction, all else being equal, compared to products receiving more active WOM, products with less active WOM end up with a lower chance to attract future consumers' attention, leading to fewer sales. In other words, the success of a product on the third-party websites may potentially have a negative impact on future sales. This finding calls for further investigations on the potential conflicts of various types of services provided by online third-party channel with online retail channel.

Our results also have valuable managerial implications. First, online marketers are recommended to utilize external WOM as an efficient strategy to promote sales. Online internal WOM has been well recognized for its similar or even more significant power as advertising, which has motivated marketers to allocate firm resources to encourage consumers' sharing behaviors. Our results further suggest that online retailers or manufacturers could form alliance with third-party websites in stimulating consumer reviews and inviting experts to give comments. The availability of external WOM would benefit their WOM marketing strategy on retail websites. Second, retailers or manufacturers are warned of the risk of engaging in free-trial services on third-party websites. Recently online retailers have started considering the partnerships with third-party websites (Jupiter Research 2005). However, our results suggest that not all the contents on third-party websites are beneficial to online retail sales. For example, user reviews and professional reviews are the much better choices than free-trial services to invest in. Third, third-party information should be incorporated into forecasting retail sales. Previous studies have suggested that the endogeneity of WOM needs to be accounted for accurate estimate of retail sales (Duan et al. 2008; Godes and Mayzlin 2004). Our results further suggest that the moderation effect of third-party information on this feedback mechanism between internal WOM and retail sales shall also be included to predict retail sales.

This research has several limitations. First, our conclusions are supported by the empirical analysis of online software data and needs to carefully extend to other contexts. Consumer behavior for software programs as an example of experience goods could be different from consumer behavior for search goods (Huang et al. 2009). Gu et al. (2011) also argued that the impacts of internal and external WOM depend on product involvement. Therefore, it would be interesting to extend this study to a broader context with more product types involved. Second, our current empirical analysis is based on only 14 weeks of data. Although we adopt the Bayesian framework to more rigorously handle the finite sample size, part of the insignificant results may very likely suffer from the small sample issues. In addition, the sample size also limits our ability to integrate more variables into the model in order to consider the impact of more types of information on third party websites. It is, therefore, crucial to use a richer data set over a longer collection period to obtain more robust estimates. Third, our study identifies the moderation effect of third-party information from one single third-party infomediary on the feedback mechanism of internal WOM and retail sales. Nevertheless, consumers may also search on more third-party infomediaries before proceeding to retail websites. It would be thus interesting to compare the moderation effect of third-party information from various third-party websites. Fourth, our empirical model only captures consumer behavior on Amazon after referring to CNETD. However, there is also a chance that consumers may end up purchasing software programs or sharing their feedback on other websites or even through offline channel. As a result, the identified moderation effect of third-party information on the dynamics between internal WOM and retail sales could be slightly underestimated. It also calls for a further comparison of the moderation effect of third-party information on retail websites with distinct market share or different design of recommendation system. Moreover, although the literature suggests that consumers search for external WOM before arriving at retailer websites, we do not directly observe such consumer behavior. A promising extension of this research could look into this process from the perspective of consumer search cost. Last but not least, our current model only tested limited types of information on CNETD. Future expanded investigation would integrate more information such as valence, volume, variance of user reviews, disagreement between user and professional reviews, and user review content.

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