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ABSTRACT

Free sampling of information goods has become a common business practice in expectation of reducing consumers' uncertainty of product quality and helping product diffusion, yet receiving limited investigation of how consumers process free sampling and online word-of-mouth (WOM) and its consequences on retail sales. In this research, we examine the impact of free sampling of information goods on the dynamics of online WOM and retail sales by analyzing a simultaneous equation system in a Bayesian hierarchical framework in online software market. We find that free sampling of information goods asymmetrically moderates the positive feedback mechanism between online WOM and retail sales. More adoptions of free trial not only directly lead to more retail sales but also enhance online WOM effect. Nevertheless, more adoptions of free trial generate fewer WOM and weaken the impact of past sales on WOM, which could potentially have a negative impact on future sales.

Keywords

Free sampling, information goods, software free trial, word-of-mouth, simultaneous equation, Bayesian framework

INTRODUCTION

Free sampling of physical products has been widely adopted as an effective promotion tool in addition to advertising. Many companies distribute free samples in store, advertising events, etc. This strategy is generally believed to boost sales because of its expansion effect and acceleration effect. The free trial experience stimulates purchasing by consumers who would not consider buying the product without trying out a sample; providing free samples also encourages consumers to purchase the product earlier than they would otherwise (Bawa and Shoemaker, 2004). Free sampling of physical goods, nevertheless, may risk cannibalizing some demands of the commercial product since consumers would otherwise have purchased the commercial product to try it. In recent years, free sampling strategy has also been extended to information goods along with the popular electronic marketplaces. For example, Amazon provides free preview of a limited chapter for some books; iTunes stores list free songs and free videos of broad categories; CNETD (CNET www.download.com) organizes hundreds of free trial versions of software programs.

However, different attributes of free sampling between physical goods and information goods calls for an independent research on consumers' reactions to free sampling of information goods. On the one hand, free sampling of information goods could be more effective than free sampling of physical goods in enhancing sales. Free samples of physical goods differ from the commercial versions in quantity. Yet, free trials of information goods could be differentiated from commercial products by quality. For example, software free trial often has limited functionalities of the commercial software. In this sense, the quality distinction may reduce the cannibalization effect of free sampling for information goods. In addition, the purpose of free sampling has different focus between physical goods and information goods. Free samples of physical goods mainly aim to bring consumers into purchasing cycle while free trials of information goods help consumers reduce uncertainty about the products as a direct experience before consumptions (Wang and Zhang, 2009). Information goods are mostly experience goods whose values are hard to evaluate until they can be consumed (Nelson, 1970). From this perspective, free sampling plays a more important role in helping consumers find matched information goods. On the other hand, free sampling of information goods may suffer more severely from the cannibalization effect than free sampling of physical goods. The marginal cost for information goods is almost zero, much lower than that for physical goods. The development of broadband access and personal computer also extends the reaching range of free sampling of information goods. This makes free sampling of information goods a more economical and feasible strategy for companies as a promotion tools. However, the more widely accessed free trials of information goods may risk losing more demands for commercial information goods due to cannibalization. Therefore, there is an essential need to bring empirical evidence in academic research to re-examine the impact of free sampling on consumer behavior in the territory of information goods.

In this paper, we aim to investigate this under-explored area by investigating the mechanism underlying the impact of free sampling of information goods on consumers' online Word-of-Mouth (WOM) activities and their purchasing decisions. Specifically, we not only examine the direct impact of free sampling of information goods on retail sales and online WOM but also examine its moderation effect on the dynamics between WOM and online retail sales. Using a 25-week panel data of software free sampling on CNETD as well as the sales ranks and user review information for the matched commercial software programs on Amazon (www.amazon.com), we empirically analyze a simultaneous equation system in a Bayesian hierarchical framework to model the feedback mechanism between WOM and retail sales, the moderation effect of software free sampling on this feedback mechanism, and the direct impacts of software free sampling on WOM and sales. We find that free sampling of information goods asymmetrically moderates the positive feedback mechanism between online WOM and retail sales. A larger number of CNETD free software downloads not only directly lead to more Amazon sales but also enhance the positive impact of Amazon WOM on Amazon sales. However, we find that more downloads of CNETD software free trial directly discourage Amazon WOM activities and also weaken the positive impact of the past Amazon sales on Amazon WOM, which may potentially have a negative impact on future sales.

The rest of paper proceeds as follows. The theoretical background is introduced in the next section, which is followed by the data description. We then describe and analyze the empirical model. In the last section, we discuss the results and implications.

THEORETICAL BACKGROUND

Direct impact of free sampling of information goods

The literature regarding free sampling of physical goods imply that free sampling of information goods may influence sales and online WOM activities. As briefly discussed in introduction, similarly as free sampling of physical goods, free sampling of information goods can also have expansion effect, acceleration effect and cannibalization effect on sales. Its expansion effect might be even more significant than free sampling of physical goods. Consumers often face large uncertainty while dealing with information goods, most of which are experience goods with values hard to evaluate before consumptions. Hence, free sampling of information goods provides consumers opportunities to directly experience the full or limited functionalities of commercial products before purchases, which significantly reduces their uncertainty to make good choices. In terms of cannibalization effect, however, the attributes of free sampling of information goods could lead to two contradictory arguments. The quality distinction between free trial and commercial product of information goods may reduce the cannibalization effect while the easier access to free trial of information goods for consumers may strengthen the cannibalization effect.

Moreover, free sampling of information goods may also influence consumers' purchasing intentions of commercial products, which influences their further decisions of whether to participate in online WOM activities. Consumers' willingness to originate product-related conversation is explained as a function of involvement (Dichter, 1966). Consumers' experiences of free trials would lead to the formation of intentions regarding whether to buy the commercial products. Consumers who have positive intentions should more tend to communicate their thoughts because they could realize self-satisfaction by sharing their sense of commitment with others (Homes and Lett, 1977).

Moderation effect of free sampling of information goods

Previous research suggest that consumers' participations in online WOM activities and purchasing behaviors on retail websites could be explained by a positive feedback mechanism (Duan, Gu and Whinston, 2008; Godes and Mayzlin, 2004). Online WOM may enhance consumer awareness of the relevant product, leading to more sales, which is often termed as online WOM effect; while more past sales indicate a larger user base, leading to more user-generated WOM activities. We propose that free sampling of information goods moderates this positive feedback mechanism.

The proposed moderation effect is expected to be two-way. First, free sampling of information goods is anticipated to moderate the impact of volume of online WOM on retail sales. More adoptions of free sampling of information goods help introduce the product to consumers and obtain a larger user base for free trial version, which could generate broader discussions among consumers. Consumers may take the popularity of free trial version as an indicator for the popularity of the corresponding commercial product. Since popular products are inclined to receive more WOM, consumers feel more confident that they can find their WOM information, which motivates them to search for online WOM of those products more. Therefore, more searches on WOM enhance the effectiveness of WOM on sales.

Second, free sampling of information goods is expected to moderate the impact of past retail sales on volume of online WOM. The underlying rationale behind the positive impact of past retail sales on volume of online WOM is that more consumers who have experienced a product lead to more WOM. Yet, not all the consumers have the same incentives to communicate their experiences after consumptions. Consumers share their feedback partly to enhance their own self-worth (Hennig-Thurau, Gwinner, Walsh and Gremler, 2004). Consumers would expect that information goods with fewer adoptions of free trials are less popular and tend to receive a limited number of user reviews. Therefore, consumers feel more confident that their reviews would be read and their contribution would be realized by others if writing reviews on those products. As a result, for a given level of past sales, indicating a given level of user base, there are more consumers willing to share their experiences if the consumed commercial product receives fewer adoptions of free sampling.

DATA

We conduct our empirical analysis using a panel data over 25 weeks in online software market. Software programs, as one type of information goods, generally result in consumers' difficulties to observe and assess product quality before their consumptions. We collect free sampling data from CNETD weekly on all software free trials of seven categories and matched commercial software programs sold by Amazon for the period November 2010 through May 2011. These seven categories are: Antivirus Software, Corporate Security, Download Manager, File Compression, Search Tools, Web Browsers and Windows Media Player, which include categories with different application purposes.

CNETD is a leading and representative website for downloading software free trial. CNETD lists detailed product descriptions as well as weekly and cumulative download counts for each software free trial. We collect cumulative download counts for each software free trial to indicate its popularity and consumer adoption. As a particular attribute of software free sampling, software free trial could either be free version of full functionalities but for a limited trial time (freeware) or free version of limited functionalities for an unlimited trial time (trialware). Therefore, we also collect license difference, i.e. whether the software free trial is freeware or trialware, to control for the impact of free trial strategy of software companies. We also collect volume and valence of user reviews information on CNETD to control for the external WOM effect on Amazon retail sales (Gu, Park and Konana, 2011). We extract the following information on every software free trial listed in each category on CNETD at the beginning of every week: free trial name, total number of downloads, whether the free trial receives user reviews, average user rating and total number of user reviews.

We collect retail sales rank and WOM data of the matched commercial software programs from Amazon based on the "relevance" search criteria. We conduct the following matching process. For each software free trial collected on CNETD, we search for its exact name within the software department on Amazon and collect the first 60 most relevant Amazon products from the search results. Hence, one CNETD free trial might be matched up to 60 Amazon software programs, yet each collected Amazon software is matched to only one CNETD free trial with a relevance order. 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, Hu and Smith, 2003; Ghose and Sundrararajan, 2005). 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. In particular, on Amazon, we collect software name, relevance order with CNETD free trial, rank, whether receiving user reviews, average user rating, total number of user reviews, first available date, price, discount on price, and eligibility for free-shipping service.

Following Godes and Mayzlin (2004) and Liu (2006), we use one-week lagged independent variables to model the feedback mechanism between Amazon WOM and 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 causal relationship. Therefore we only keep the observations whose Amazon software programs have appeared during two consecutive weeks, which leads to our final sample of 24 weeks of panel data set. Table 1 provides the description of key variables.

CNETD (upper *c* denotes CNETD)	
$Totaldownload^{c}_{j,t}$	Cumulative number of downloads of software free trial *j* at week *t*
$Dummyfree^{c}_{j,t}$	A dummy variable measures if software free trial *j* is freeware or trialware at week *t*
Amazon (upper *a* denotes Amazon)	
$Lnrank^{a}_{i,t}$	Sales rank of software *i* at week *t* with a log transformation
$Uservolume^{a}_{i,t}$	Total number of user reviews of software *i* by week *t*
$Dummyuser^{a}_{i,t}$	A dummy variable measures if software *i* receives any user reviews by week *t*
$Urating^{a}_{i,t}$	Average user rating of software *i* by week *t*
$Relevance^{a}_{i,t}$	The relevance order of software *i* with its matched CNETD free trial at week *t*
$Age^{a}_{i,t}$	Days since software *i* has been posted by week *t*
$Discountprice^{a}_{i,t}$	Discount price of software *i* at week *t*
$Discount^{a}_{i,t}$	Discount of software *i* at week *t*
$Freeship^{a}_{i,t}$	A dummy variable measures if software *i* is eligible for free shipping at week *t*

Table 1. Description of Key Variables

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 four hierarchical 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 $Uservolume^{a}_{i,t}$ as a dependent variable and the second equation (the AmazonSales equation) includes $Lnrank^{a}_{i,t}$ 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 user reviews via the coefficient on $Lnrank^{a}_{i,t-1}$ (α_1) and the impact of volume of user reviews on retail sales via the coefficient on $Uservolume^{a}_{i,t-1}$ (β_1), when the moderation effect of free sampling is not considered.

AmazonWOM equation

$$Uservolume^{a}_{i,t} = \alpha^{c}_{0,j,t-1} + \alpha_1 * Lnrank^{a}_{i,t-1} + \alpha^{c}_{2,j,t-1} * Lnrank^{a}_{i,t-1} * (1/Relevance^{a}_{i,t-1}) + \alpha_3 * Dummyuser^{a}_{i,t-1}$$
$$+\alpha_4 * Dummyuser^{a}_{i,t-1} * Urating^{a}_{i,t-1} + \alpha_5 * Age^{a}_{i,t} + \alpha_6 * Agesq^{a}_{i,t} + \varepsilon^{a}_{i,t} \quad (1)$$

AmazonSales equation

$$Lnrank^{a}_{i,t} = \beta^{c}_{0,j,t-1} + \beta_1 * Uservolume^{a}_{i,t-1} + \beta^{c}_{2,j,t-1} * Uservolume^{a}_{i,t-1} * (1/Relevance^{a}_{i,t-1}) + \beta_3 * Dummyuser^{a}_{i,t-1}$$
$$+\beta_4 * Dummyuser^{a}_{i,t-1} * Urating^{a}_{i,t-1} + \beta_5 * Age^{a}_{i,t} + \beta_6 * Agesq^{a}_{i,t} + \beta_7 * Discountprice^{a}_{i,t}$$
$$+\beta_8 * Discount^{a}_{i,t} + \beta_9 * Freeship^{a}_{i,t} + \delta^{a}_{i,t} \quad (2)$$

CNETD hierarchical direct impact equations

$$\alpha^{c}_{0,j,t-1} = \phi_1 * Logtotaldown^{c}_{j,t-1} + \phi_2 * Dummyfree^{c}_{j,t-1} + \zeta^{c}_{j,t-1} \quad (3)$$

$$\beta^{c}_{0,j,t-1} = \varphi_1 * Logtotaldown^{c}_{j,t-1} + \varphi_2 * Dummyfree^{c}_{j,t-1} + \varphi_3 * Uservolume^{c}_{j,t-1} + \varphi_4 * Urating^{c}_{j,t-1} + \xi^{c}_{j,t-1} \quad (4)$$

CNETD hierarchical moderation equations

$$\alpha^{c}_{2,j,t-1} = \gamma_1 * Logtotaldown^{c}_{j,t-1} + \gamma_2 * Dummyfree^{c}_{j,t-1} + \omega^{c}_{j,t-1} \quad (5)$$

$$\beta^{c}_{2,j,t-1} = \lambda_1 * Logtotaldown^{c}_{j,t-1} + \lambda_2 * Dummyfree^{c}_{j,t-1} + \upsilon^{c}_{j,t-1} \quad (6)$$

$$\begin{bmatrix} \varepsilon^{a}_{i,t} \\ \delta^{a}_{i,t} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sum^{a}_{\varepsilon\varepsilon} & \sum^{a}_{\varepsilon\delta} \\ \sum^{a}_{\delta\varepsilon} & \sum^{a}_{\delta\delta} \end{bmatrix} \right), \; \xi^{c}_{j,t-1} \sim N(0, \sum^{c}_{\xi\xi}), \; \zeta^{c}_{j,t-1} \sim N(0, \sum^{c}_{\zeta\zeta}),$$

$$\omega^{c}_{j,t-1} \sim N(0, \sum^{c}_{\omega\omega}), \; \upsilon^{c}_{j,t-1} \sim N(0, \sum^{c}_{\upsilon\upsilon})$$

In addition, we conduct a pair of two hierarchical moderation equations (equations 5 & 6) to model the moderation effect of CNETD free trial 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 $Lnank^{a}_{i,t-1} * (1/Relevance^{a}_{i,t-1})$ in the AmazonWOM equation and $Uservolume^{a}_{i,t-1} * (1/Relevance^{a}_{i,t-1})$ in the AmazonSales equation respectively. As described beforehand in data collection, each i^{th} Amazon software is matched to a j^{th} CNETD free trial with a relevance order ($Relevance^{a}_{i,t-1}$). Since the i^{th} Amazon software might not be exactly the commercial version of j^{th} CNETD free trial, we assume that the moderation effect from j^{th} CNETD free trial on i^{th} Amazon software should be more significant when these two are more relevant. Note that closer relevance leads to a smaller value of $Relevance^{a}_{i,t-1}$. As a result, we include the inversed relevance order $(1/Relevance^{a}_{i,t-1})$ to shape the moderation effect.

Specifically, we allow the coefficients on $Lnrank^{a}_{i,t-1} * (1/Relevance^{a}_{i,t-1})$ ($\alpha^{c}_{2,j,t-1}$) and $Uservolume^{a}_{i,t-1} * (1/Relevance^{a}_{i,t-1})$ ($\beta^{c}_{2,j,t-1}$) to be heterogeneous over the j^{th} CNETD free trial every week, leading to two hierarchical moderation equations. The two error terms in these two equations ω and υ could control for other omitted free sampling information on CNETD or other websites offering software free sampling that consumers may experience besides CNETD's. If adopting the conventional approach of using interaction term, the moderation effects of omitted information would be retained in the error terms of AmazonWOM and AmazonSales equations. These moderation effects would then correlate with $Lnrank^{a}_{i,t-1}$ in the AmazonWOM equation and $Uservolume^{a}_{i,t-1}$ 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. Consumer adoption of j^{th} CNETD free trial is measured by its number of total downloads. We apply a log transformation on total downloads ($Logtotaldown^{c}_{j,t-1}$) in order to convert the value to a comparable magnitude to other variables. We also include a dummy variable to indicate whether the j^{th} CNETD free trial is a freeware ($Dummyfree^{c}_{j,t-1}$). Free trial strategy is always a central issue in software industry and which version of software free trial to offer has been shown to significantly influence consumer behaviors (Cheng and Liu, 2011), hence it would be important to control for the impact of license difference. By estimating the whole model system, we would be able to show the moderation effect of free sampling on the feedback mechanism between volume of WOM and online retail sales by monitoring one pair of coefficients: the coefficient on $Logtotaldown^{c}_{j,t-1}$ in equation 5 (γ_1) and the coefficient on $Logtotaldown^{c}_{j,t-1}$ in equation 6 (λ_1).

Similarly, we also build two other hierarchical equations to model the direct impacts of free sampling on volume of Amazon user reviews and Amazon sales respectively. We allow two constant terms in the AmazonWOM equation ($\alpha^{c}_{0,j,t-1}$) and the AmazonSales equation ($\beta^{c}_{0,j,t-1}$) random to vary over the j^{th} CNETD free trial every week, leading to two hierarchical direct impact equations (equations 3 & 4). Similarly as equations 5 & 6, we also include $Dummyfree^{c}_{j,t-1}$ in addition to $Logtotaldown^{c}_{j,t-1}$ in both two equations. We also include CNETD WOM information in the AmazonSales equation to control for the external WOM effect on Amazon sales (Gu et al., 2011). Hence, volume and valence of CNETD user reviews ($Uservolume^{c}_{j,t-1}$, $Urating^{c}_{j,t-1}$) are added in equation 4.

Following previous studies, we 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; Zhou and Duan, 2011). Hence, for the AmazonSales equation, we include the information related with valence of Amazon WOM ($Dummyuse^{a}_{i,t-1}$, $Urating^{a}_{i,t-1}$). In addition, price effects are controlled by the discount price $Discountprice^{a}_{i,t-1}$ and the value of offered discount $Discountp^{a}_{i,t-1}$. A dummy variable $Freeship^{a}_{i,t-1}$ is used to control for the difference in availability of free-shipping service among the collected software programs. We also use product age $Age^{a}_{i,t-1}$ and the quadratic term of product age $Agesq^{a}_{i,t-1}$ to control for product diffusion (Duan et al., 2009). $Age^{a}_{i,t-1}$ and $Agesq^{a}_{i,t-1}$ are also included in the AmazonWOM equation. We also include information about valence of Amazon user reviews ($Dummyuser^{a}_{i,t-1}$, $Urating^{a}_{i,t-1}$) in the AmazonWOM equation as suggested by Duan et al. (2008).

Results

We estimate our model system using Markov chain Monte Carlo method on the pooled data of seven categories. 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. Table 2 shows the estimation results by the posterior means and standard deviations.

		M	SD		M	SD
AmazonWOM equation						
$Lnrank^{a}_{i,t-1}$ (α_1)		**-0.912**	0.004	$Dummyuser^{a}_{i,t-1}$ (α_2)	**-0.235**	0.010
$Urating^{a}_{i,t-1}$ (α_3)		**-0.168**	0.008			
AmazonSales equation						
$Uservolume^{a}_{i,t-1}$ (β_1)		**-0.732**	0.004	$Dummyuser^{a}_{i,t-1}$ (β_2)	**-0.322**	0.008
$Urating^{a}_{i,t-1}$ ($\beta 3$)		**-0.197**	0.006			
Correlation between errors		**0.821**	0.002			
Hierarchical moderation equations						
Eq. 5	$Logtotaldown^{c}_{j,t-1}$ (γ_1)	**3.379**	0.292	$Dummyfree^{c}_{j,t-1}$ (γ_2)	0.033	0.025
Eq. 6	(λ_1)	**-10.94**	0.833	(λ_2)	**-0.117**	0.049
Hierarchical direct impact moderation equations						
Eq. 3	$Logtotaldown^{c}_{j,t-1}$ (□$_1$)	**-13.67**	1.182	$Dummyfree^{c}_{j,t-1}$ (□$_2$)	**0.401**	0.062
Eq. 4	(φ_1)	**-12.75**	0.981	(φ_2)	**0.327**	0.065
Eq. 4	$Uservolume^{c}_{j,t-1}$ (φ_3)	0.020	0.021	$Urating^{c}_{j,t-1}$ (φ_4)	**0.185**	0.027
DIC		274850.000				
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.						

Table 2. Estimation Results of the Moderation Effect of CNETD Software Free Sampling on the Feedback Mechanism between Volume of Amazon Reviews and Amazon Sales

We first examine the feedback mechanism between volume of Amazon reviews and Amazon sales when the moderation effect of CNETD free trial is not considered. For the AmazonWOM equation, the impact of Amazon sales on its volume of user reviews is significantly positive. The coefficient on $Lnank^{a}_{i,t-1}$ (α_1) is negative, which actually indicates a positive impact, 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 $Uservolume^{a}_{i,t-1}$ (β_1). Therefore, a positive feedback mechanism explains the dynamics between online WOM and retail sales, which is consistent with prior findings.

We now proceed to discuss the moderation effect of software free sampling on this identified positive feedback mechanism. We find that in the first hierarchical moderation equation (equation 5), the coefficient (γ_1) on total downloads ($Logtotaldown^{c}_{j,t-1}$) is positive and significant. The significantly positive γ_1 reduces the magnitude of the negative coefficient α_1 in the AmazonWOM equation of the simultaneous equation system. Hence, given the negative linear relationship between the log values of rank and log values of sales, this shows that consumer adoption of software free sampling negatively moderates the impact of past sales on online WOM activities as we expected. Consumers are more willing to share their feedback for commercial software programs with less adoptions of software free trial, indirectly leading to more sales afterwards. On the other hand, the estimation result of significantly negative λ_1 in the second hierarchical moderation equation (equation 6) implies that consumer adoption of software free sampling positively moderates online WOM effect. The negative value of the coefficient λ_1 adds to the magnitude of the negative coefficient β_1 in the AmazonWOM equation. This indicates that consumers are more significantly influenced by online WOM to make more purchases of commercial software programs when those commercial products receive more adoptions of software free sampling, leading to more WOM activities afterwards. Overall, those results provide evidence that free sampling of information goods asymmetrically moderates the positive feedback mechanism between online WOM and retail sales.

In addition, we also examine the direct impact of free sampling on online WOM and retail sales based on the estimation results of equations 3 &4. The coefficient on $Logtotaldown^{c}_{j,t-1}$ ($\square_1$) in equation 3 is significantly negative, indicating that fewer adoptions of software free trial directly generate more WOM activities. This is consistent with the research regarding the underlying motivation of consumers' online WOM activities (Hennig-Thurau et al., 2004). Fewer adoptions of software free trial indicate lower popularity of its corresponding commercial product, which sends consumers a signal of relatively fewer extant WOM activities of the commercial product. Hence, consumers are more motivated to write reviews on this commercial product for a higher chance to differentiate their reviews and highlight their expertise. The coefficient on $Logtotaldown^{c}_{j,t-1}$ (φ_1) in equation 4 is significantly negative, which implies that more adoptions of software free trial directly lead to more retail sales, given the negative linear relationship between the log values of rank and log values of sales. This result suggests that overall promoting free sampling of software program directly attracts more demands than cannibalizes demands.

We also notice some interesting results regarding the license difference of software free trial. Based on the estimation results of equation 5, it seems the license difference does not moderate the impact of past sales on online WOM, indicated by the insignificant coefficient on $Dummyfree^{c}_{j,t-1}$ (γ_2). However, the positive $\square_2$ in equation 3 implies that freeware outperforms trialware in directly originating online WOM of commercial software programs. Homes and Lett (1977) found that consumers with positive purchasing intent after trying out free trials more likely share their feedback. Hence, this result further suggests that consumers who tried out freeware may have more positive purchasing intentions, and thus leading to more online WOM of commercial software programs. On the other hand, the more positive purchasing intentions of consumers resulted from trying out freeware do not necessarily directly lead to more sales. We find that trialware beats freeware in directly promoting sales, indicated by the positive φ_2 in equation 4. One of the reasons could be that although freeware results in more positive purchasing intentions than trialware, consumers may get satisfied with freeware already and simply continue to use freeware for it does not have any time limitation. We also find that license difference of software free sampling positively moderates the online WOM effect, indicated by the significantly negative coefficients λ_2 in equation 6. The impact of online WOM activities on retail sales is stronger for commercial software with available freeware.

Finally, we check the robustness of our model by including six dummy variables for 7 categories in each of four hierarchical equations (equations 3, 4, 5 & 6). All the dummy variables are insignificant in each equation and the estimation results of all other coefficients are qualitatively the same.

CONCLUSION REMARKS

To our best knowledge, this study is the first to examine the moderation effect of free sampling of information goods on the dynamics between online WOM and retail sales. We find that consumer adoption of free sampling asymmetrically moderates the positive feedback between online WOM and retail sales. Free sampling of information goods not only directly leads to more retail sales but also enhances online WOM effect, which suggests that more adoptions of free sampling boost sales in the short run. Nevertheless, it directly generates fewer WOM and weakens the impact of past sales on online WOM, which could potentially have a negative impact on future sales. Therefore, no deterministic conclusion can be drawn regarding whether promoting free sampling of information goods benefits sales in the long run. Our results also shed some lights on the free trial strategy for software companies. We find that license difference of software free trial positively moderates WOM effect. Freeware directly leads to more WOM and fewer sales than trialware while commercial software programs with available freeware are more influenced by online WOM.

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