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The interplay between free sampling and word of mouth in the online software market

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ABSTRACT

Free sampling in digital format has become a common business practice in the online market offering consumers first-hand experience with products, due to its low marginal cost and extensive online distribution. At the same time, online word of mouth (WOM) has also been a prevalent strategy on the Internet for increasing product visibility and providing trustworthy product information. Those two online marketing strategies are generally considered to stand alone by marketers and prior research. Nevertheless, by drawing on integrated information response theory as well as theories for explaining online consumers' review sharing, we argue that free sampling complements WOM in the online market by amplifying its sales effect and facilitating its implementation. We provide supportive empirical evidence through a Bayesian analysis of software free sampling on CNET Download.com (CNETD) and sales and WOM from Amazon.com over a 25-week data set. Our results show that adoptions of CNETD free sampling positively interact with Amazon WOM in influencing Amazon software sales. In addition, more adoptions of CNETD free sampling lead to a larger volume of Amazon WOM, and this impact is more significant for less popular products. These findings contribute to our understanding of free sampling in the online market such that, in addition to its direct sales effect, free sampling can also potentially affect sales through influencing online WOM. Therefore, we suggest that marketers evaluate the free sampling strategy by including its interplay with online WOM and apply low-cost free sampling to facilitate the relatively more expensive online WOM marketing strategy, especially for unpopular products.

1. Introduction

Free sampling is not a new strategy for promoting products. In the traditional offline market, it has been widely applied towards marketing physical products, such as distributing free samples of toothpaste in small quantities at grocery stores. This strategy is generally believed to affect sales positively by stimulating and encouraging purchases, and negatively by cannibalizing some consumer demand [4]. As a natural extension of this practice to the online market, many vendors have been offering free samples in digital format,[2] such as music files, mobile apps, downloadable software, and Internet videos. For example, Amazon provides free previews of some book chapters; iTunes store lists free songs and free videos across broad categories; CNETD (CNET www.download.com) hosts hundreds of software free trials for download. As compared to the offline market, free sampling in the online market is used more extensively and considered to be more efficient, partly because of the low marginal cost of digital production and the ease of distribution through broadband Internet [41]. In addition, those products that offer free sampling in digital format are normally in the category of experience goods, whose quality is difficult to evaluate before consumption. Therefore, free sampling in the online market provides consumers with convenient access to direct experience of product quality, at least in part [9,27].

In addition to free sampling, the challenge for selling experience goods online also involves online Word-of-Mouth (WOM) marketing to facilitate online consumers' search and product assessment. More than half of firms in a recent survey reported that they have already adopted online WOM in their marketing campaigns, and 20% to 50% of sales are reported to be affected by online WOM [5,42]. WOM is created by consumers themselves and thus is trustworthy and effective in affecting online market outcomes, as demonstrated by both industry surveys and academic research [10,14,20,27,29,31,45,46]. In particular, WOM volume, which is normally measured by the total number of online user reviews, is known to help the corresponding product stand out from the nearly overwhelming product choices online [13,29].

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[2] In this paper, we define free sampling in the online market as free samples in digital format that are provided and experienced through online platforms. In the remainder of this paper, we may use the phrases *free sampling in digital format* and *free sampling in the online market* interchangeably.

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It is natural to ask whether and how free sampling in digital format and online WOM marketing practices interplay in today's online market. The closest answer we can resort to is from the offline market. In the offline context, a negative interaction effect has been found between free sampling and advertisement in affecting market outcome [30,39]. Will such an interplay also exist between free sampling and WOM in the online market, where free sampling is more extensively adopted and WOM is believed as a more effective "advertisement" [31,41,42]? This is a crucial question, because free sampling in digital format is so inexpensive that it can easily be widely implemented, and at the same time more than 70% of the firms are committed to increasing spending on online WOM in the future [42]. It is important for firms to have an in-depth understanding of how low-cost free sampling can influence the effectiveness of their heavily funded WOM marketing strategies in the online market. Nevertheless, few studies in the past have been dedicated to address this issue. The relevant literature mainly looks at free sampling and WOM as two isolated and stand-alone strategies in the online market. Therefore, we wished to study this under-explored area by specifically investigating (1) how the interplay between free sampling in digital format and online WOM affects online retail sales; and (2) how free sampling in digital format affects the volume of online WOM.

To do so, we collected a 25-week panel data set of software free sampling on CNETD as well as the sales ranks and WOM information of the corresponding commercial software programs on Amazon (www.amazon.com). We empirically analyzed the interplay between CNETD free sampling and Amazon WOM by constructing seemingly unrelated equations in a Bayesian hierarchical framework. We found that in the online software market, free sampling amplifies the sales effect of online WOM. Moreover, more adoptions of software free trials on CNETD also directly lead to more Amazon WOM. Increasing CNETD free trial downloads by 10% can boost the number of Amazon user reviews by 3%, and this impact is more significant on less popular products. Therefore, overall we have found that, in the online software market, free sampling complements online WOM marketing, not only by enhancing its impact on sales but also by attracting more active WOM.

Our results contribute to the literature mainly from the following aspects. First, the finding of the complementary relationship between free sampling and online WOM highlights the importance of examining distinct marketing strategies in a systematic way, instead of separately, to obtain a fuller picture of their impacts. This is especially important for understanding the online market, where the wide reach of the Internet and the convenience of digitalization make it possible that customers are exposed to various internet marketing strategies simultaneously and are aware of others' adoptions of those promotions. Second, they add to our understanding of free sampling in the online market. While relevant prior studies on free sampling in digital format primarily focus on either its direct effect on market outcome or its license strategy [9,11,27,41], we offer a different angle to interpret the role that free sampling plays in the online market. We provide empirical evidence that free sampling in the online market can indirectly affect retail sales in two different ways that have not been revealed before. A large number of consumer adoptions of free sampling in digital format can strengthen the sales impact of online WOM. Free sampling in digital format also encourages more consumers to write reviews online, especially for less popular products, and this in turn potentially affects online retail sales. Third, this study also contributes to the literature with regard to the generation of online WOM. We applied two different theories on the underlying motivation behind consumers' online experience sharing and find that involvement theory dominates self-enhancement theory in our context [12,23]. We will elaborate this discussion in our hypotheses development as well as our empirical results. Lastly, our results also shed some lights on long tail research that studies the heterogeneity of online user choices towards the tail products [1,7,44]. Online search tools, abundant product options, and online WOM are believed to promote the niche market, i.e., the market for the tail products. We find that free sampling in the online market can also be an influencing factor on the formation of the long tail. Our results show that free sampling in digital format is favorable to less popular products by helping attract more user reviews.

The rest of paper proceeds as follows. Section 2 discusses the related literature and its differences from the current study; Section 3 presents the hypotheses development. The research context and data are discussed in Section 4. We then describe the empirical model and analyze the results. In the last section, we summarize the findings, discuss the managerial implications, and include limitations and future research directions.

2. Related literature

This study mainly draws on three streams of research: (1) the literature on free sampling in the online market; (2) the literature on the interaction of free sampling with other marketing strategies; and (3) the literature regarding the generation of online WOM.

The majority of the literature regarding free sampling in online platforms focuses on its impact on online market outcomes. As a natural extension from studying free sampling in the offline market [4], free sampling in the digitalized context is similarly shown to have two opposite effects on market outcomes, evidenced by analytical and empirical examinations [2,8,9,11,32,36,40,41]. On one hand, consumers may take free samples as substitutes for the corresponding commercial products. This can cannibalize consumer demand, although the inferior quality and limited trial time of free samples may limit this adverse sales effect. For example, in the online software market, the free sample either has the same full functionalities as the commercial product, but for a limited trial time (freeware) or has limited functionalities but is available forever (trialware). On the other hand, consumers get to know the product through directly experiencing the free sample, which can encourage purchases. As a distinction from those studies, our work is not designed to re-examine the sales impact of free sampling in the online market. Instead, we are interested in the interplay between free sampling in digital format and online WOM, another marketing strategy widely adopted in digital settings, in the context of the online software market. Our results suggest that evaluating the sales effect of free sampling in digital format shall also take into consideration its long-run effect, as a result of its interplay with online WOM.

In the particular software context, in recent years, a few scholars have been investigating the differential impact of free sampling license on the diffusion process of free trials, the market outcome of commercial products, and software pricing, [9,15,22,27,36,41]. For example, Lee and Tan [27] empirically studied the difference between freeware and trialware in attracting consumer adoptions of software free sampling. Wang and Zhang [41] looked into software free sampling by analytically optimizing licensing strategy. Nevertheless, we do not consider free sampling as a stand-alone marketing strategy nor focus on different software free sampling strategies. Instead, we control for free sampling license difference to rigorously reveal the interplay between free sampling and online WOM by exploring a unique data set of online WOM, consumer adoptions of software free trials, and sales.

This research is also related with another stream of the literature that studies the interaction effect between free sampling and other marketing strategies on the market outcome, mainly in the offline market. For example, scholars have generally agreed on the negative interaction effect between free sampling and advertisement in the offline market [25,30,37–39,43]. However, even in the offline market, not much attention has been paid to how offline WOM and free sampling interact to influence consumer purchase decisions, probably because user-generated WOM is limited in its amount and is difficult to collect in the offline context. This has been significantly changed in the online market. Online WOM has been a more affordable and effective promotion tool than the traditional advertisement by providing more trustworthy information and incurring lower marketing expenses [42]. Research has also shown that it significantly affects online purchases [3,10,14,20,27–29, 35,45,46]. In the meantime, free sampling in the online market is also more widely available and accessible, due to the availability of high-speed broadband Internet and the nearly zero marginal cost [41]. Therefore, it is important to understand how those two prevalent marketing strategies interplay in the online market to affect online retail sales. This study is the first to show a complementary relationship between free sampling in digital format and online WOM on online retail sales. In addition, it further looks into their interplay in more depth by studying whether and how free sampling in the online market would affect the generation of online WOM.

The next stream of relevant literature regards the theories that explain consumers' decisions on sharing feedback with others, which are cumulatively captured by volume of WOM. However, in this study we find competing inferences from those theories. One of them is proposed in the context of the offline market: Dichter's [12] involvement theory. It argues that an individual's willingness to participate in a WOM conversation heavily depends on his/her involvement. Adopting free sampling leads to high involvement. This produces consumer tension that is relieved by spreading the word about a product [12,24]. It is reasonable to apply involvement theory and expect a similar positive impact of free sampling adoption on volume of WOM in the online market. The other theory, self-enhancement theory, which has been developed and empirically tested in the online market, however, implies an opposite direction of this relationship. It proposes that consumers are motivated to write post-consumption product reviews to gain attention and enhance their images in online communities [23]. Following this theory, people may discount the contributions of reviewers, when free sampling is readily available and widely adopted by the others. Consumers can get to know products more directly from their own adoption of free sampling than indirectly from reading others' online reviews. Therefore, enhancement theory implies that widely adopted free sampling on the Internet may reduce people's willingness to share feedback on the corresponding product online, due to the lower perceived likelihood of achieving self-enhancement. Our empirical analysis contributes to this line of research by suggesting that involvement theory overweighs enhancement theory in the online software market.

3. Hypotheses

3.1. The interaction effect between free sampling and WOM in the online market

The integrated information response theory is widely applied to interpret the interaction effect between different marketing strategies that aim to promote products [30,39]. It argues a causal linkage of cognition-attitude-purchase to explain consumer reactions to various marketing strategies [38]. Cognition is defined as a recognition of the product and its attributes. Its strength level is mostly influenced by the information source, in particular, the reliability of the conveyed information. More reliable information leads to higher-order cognition and thus a more favorable attitude towards the purchase. Moreover, the impacts of multiple information sources on cognition strength contribute to the overall consumer attitude towards purchase in a nonlinear way [39]. For instance, higher-order cognition resulting from more reliable information affects consumer attitude in a nonlinear way together with lower-order cognition resulting from biased information. In other words, there is an interaction effect between two different marketing strategies, which provide product information at different reliability levels, in affecting consumer attitude and the subsequent purchase.

By applying this theory, scholars have found evidence for a negative interaction effect between advertising and free sampling in the offline market [30,37–39]. Advertisement is considered as a source of selective and biased information, because it is solely created by firms and marketers. Consumers tend to mistrust or discount the information introduced by advertisement. Therefore, advertisement produces lower-order cognition and less favorable attitude towards purchase. On the contrary, free sampling provides consumers with direct experience of product quality. It is the individual consumer's decision of whether to adopt the free sample. As a result, people trust the information behind prior consumers' adoptions and the information learned directly from their own experiences of free sampling. According to the integrated information response model, the more reliable information through free sampling results in higher-order cognition and more favorable attitude towards purchase. Therefore, higher-order cognition resulting from free sampling and lower-order cognition resulting from advertisement lead to a negative interaction effect between those two marketing strategies on consumer purchases [30,39].

Following this theory, we argue that free sampling in digital format and online WOM complement each other in affecting online purchase. On online platforms, consumers are easily aware of how many people have already tried out free samples and how many people have shared feedback online. Those sources of information are created by consumers, instead of vendors or advertisers, and thus are considered reliable. More active online WOM attracts consumer attention and helps reveal trustworthy product information from prior users; therefore, unlike advertisement, the volume of online WOM can result in higher-order consumer cognition. In addition, similarly to the offline market, free sampling in the online market leads to consumers' higher-order cognition on the corresponding product, because consumers make their own decisions to adopt free sampling. Based on integrated information response theory, the higher-order cognition produced individually by those two different information sources leads to favorable consumer's attitude towards purchase in a nonlinear manner. In other words, WOM and free sampling in the online market positively interplay to affect consumers' attitudes and their subsequent purchases. Thus, we propose:

H1. Free sampling adoption and volume of WOM in the online market have a positive interaction effect on online retail sales.

3.2. The impact of free sampling on the generation of WOM in the online market

As discussed in Section 2, Ditcher's involvement theory implies a positive impact of free sampling on the generation of WOM in online platforms [12]. Consumers talk to others online by sharing feedback in order to ease their tension, which is caused by high-level involvement through their first-hand experience of free sampling. This is already supported in the offline market by an empirical study conducted nearly four decades ago that consumers who have adopted free samples will more likely share their opinions than those who don't try free samples [24]. Therefore, following this stream of literature, we would expect that this positive relationship between free sampling and volume of WOM may also exist in the online market.

Nevertheless, self-enhancement theory that has been tested in online platforms implies the opposite, i.e., a negative impact of free sampling on volume of online WOM [23]. Self-enhancement is defined as peoples' emotional desire to gain attention and enhance their images among others [23]. Hennig-Thurau et al. [23] theorized and empirically demonstrated that self-enhancement has a significant positive impact on the number of comments in online opinion platforms. When people perceive that others would appreciate their expertise and contribution through reading the reviews, they are more willing to write reviews online. We attempt to apply this theory to interpret the impact of free sampling on the generation of WOM in online market. The large volume of free sampling adoptions indicates that a great deal of people have already known the product through their own trial experiences in the online market. Therefore, the value of online WOM then tends to play a less significant role in providing product information, especially given that WOM conveys product information in a less direct way than free sampling. Accordingly, people perceive a lower likelihood to enhance

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self-image in the online community through writing reviews on products whose free samples in digital format have already been widely distributed and experienced. In this case, consumers are less willing to write reviews on those products. Their willingness to write reviews can be cumulatively captured by volume of WOM. Therefore, self-enhancement theory implies that, in the online market, free sampling adoptions have a negative impact on volume of WOM.

To our best knowledge, there is little theory to draw on for determining which of above two opposite forces is dominant in the online market. As a result, we'll leave this question to empirical investigation by testing the following two competing hypotheses.

H2a. Free sampling adoption has a positive impact on volume of WOM in the online market.

H2b. Free sampling adoption has a negative impact on volume of WOM in the online market.

In addition, involvement theory further argues that the impact of free sampling on WOM in the online market varies over superstar and underdog products. In essence, this theory implies that, if people foresee that their reviews are more likely to be needed, and thus read and valued, they can perceive a greater likelihood of confirming their discovery of the product to others, so that they can ease tensions caused by their free sampling experience [12]. In the online market, as suggested by the long tail literature, WOM on less popular products is more resorted to and valued, as a result of an extraordinarily wide product assortment and consumers' niche preferences [1,7,44]. Armed with various search tools, consumers in the online market now have the need and the capability to more extensively search for and rely on the reviews of less popular products, which tend to receive fewer discussions and limited product information online [1]. Accordingly, people who write reviews to ease their tension caused by the free sampling experience in the online market are more motivated to participate in online WOM activities of less popular products. As a result, we propose:

H3. The impact of free sampling adoption on volume of WOM in the online market is more significant for less popular products.

4. Data

4.1. Research context

We conducted our empirical analysis using panel data over 25 weeks in the online software market. A software program is essentially born in the digital format. Therefore, the marginal cost of producing an additional piece of software for free trial is nearly zero, which encourages the prevalent practice in the online software market of adopting a free sampling marketing strategy [41]. Meanwhile, most of the software retail websites also readily post reviews generated by prior consumers, hoping to benefit from online WOM marketing. Those two marketing strategies are believed to help with the difficulty of observing and assessing product quality of software programs before consumption, which is a common issue for experience goods. To shop for software as a particular type of experience goods, consumers have the incentive to try out the free trial for first-hand experience and extensively search online WOM as a significant source of product information. Those software consumers are also generally equipped with the necessary hardware and computer skills to do so. Therefore, the online software market is a suitable context where we can delve into the interplay between those two marketing strategies.

In particular, we collected weekly free sampling data from CNETD on software free trials in seven categories and, at the same time, also collected data on matched commercial software programs sold by Amazon during the period November 2010 through May 2011. Amazon is among the most popular electronic commerce sites in the United States and thus has been frequently chosen by prior studies to examine online consumer purchase behavior [10]. CNETD was chosen as a leading and representative platform that provides software free sampling in the form of digital downloading [27]. It lists detailed product descriptions as well as weekly and cumulative download counts for each software free trial and has been adopted by previous studies for investigating free sampling in the online market [27]. Given the software consumers' familiarity with information technology and the availability of various online tools (e.g., search engines), we believe it is reasonable to assume that Amazon software consumers are very likely aware of the CNETD platform, which is also evidenced by the literature [21,34].

Specifically, the seven categories on CNETD that we studied are: Antivirus Software, Corporate Security, Download Manager, File Compression, Search Tools, Web Browsers, and Windows Media Player, which includes categories with different application purposes. We picked those seven categories to ensure that we have a large and diversified coverage to explore our research questions, as each of the seven categories has a distinct application purpose and serves as an individual market. Prior studies have also shown that these categories account for a large portion of the popular products in the software market [14]. Therefore, we believe our data from those seven categories is suitable to empirically investigate our hypotheses regarding the interplay between free sampling and online WOM.

On CNETD, we collected cumulative download counts for each software free trial to capture its consumer adoption. As mentioned beforehand, being a particular attribute of software free sampling, software free trial could be in the form of either freeware or trialware licenses [27]. Therefore, we also collected the license difference of each free trial. In addition to the total number of user reviews, we also collected average user rating on CNETD, as CNETD WOM has been shown to affect Amazon retail sales [21]. Overall, at the beginning of every week, we extracted the following information on every software free trial listed in each of seven categories on CNETD, in addition to the technical specifications: free-trial software name, total number of downloads, whether the free trial received user reviews, average user rating, and total number of user reviews.

On Amazon, we mainly collected retail sales rank and WOM data for software programs that were matched to the CNETD free trials. We conducted the following matching process based on the "relevance" search criterion at the beginning of every week. For each software free trial collected on CNETD that week, we searched for its exact name within the software department on Amazon and collect the first 70 most relevant Amazon products from the search results. We used the ordering number in the list of matched results to measure the relevance of the corresponding Amazon software to the CNETD free trial. For example, a relevance of "1" indicates this Amazon software is ranked as the number one of the matched results and is thus the best match to the corresponding CNETD free trial. Accordingly, one CNETD free trial can be matched to up to 70 Amazon software programs. We also observed that, overall, each collected Amazon software is matched to only one CNETD free trial. This helps show the appropriateness of this approximate matching mechanism, which avoids the tedious weekly manual checking yet can still comprise a large data set of free sampling and online WOM. As a robustness test, we also conducted analyses on two different subsamples that only include the top one matched and top five matched Amazon products, respectively. The details will be elaborated in Section 5. Particularly, every week we collected software name, relevance order with CNETD free trial, sales rank, total number of user reviews, average user rating, first available date, price, and eligibility for free-shipping service. Table 1 provides the description of variables collected on both two sites.

4.2. Key variables

We used three key variables to capture the Amazon sales ($-LogRank_{\bar{i},t}{}^{a}$), Amazon user-generated WOM ($LogUservolume^{a}{}_{i,t}$), and adoptions of CNETD free trial ($LogDownload^{c}{}_{j,t-1}$), respectively. 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,

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Table 1
Variable descriptions.

CNETD (superscript *c* denotes CNETD)	
j	CNETD free trial j
$Download^c_{j,t}$	Cumulative number of downloads of software free trial j at week t
$Dummyfree^c_{j,t}$	A dummy variable that measures if software free trial j is freeware or trialware at week t
$Uservolume^c_{j,t}$	Total number of user reviews of software free trial j at week t
$Dummyuser^c_{j,t}$	A dummy variable that measures if software j receives any user review by week t
$Urating^c_{j,t}$	Average user rating of software free trial j at week t
Amazon (superscript *a* denotes Amazon)	
i	Matched Amazon Software i
$Rank^a_{i,t}$	Sales rank of software i at week t
$Uservolume^a_{i,t}$	Total number of user reviews of software i at week t
$Dummyuser^a_{i,t}$	A dummy variable that measures if software i receives any user reviews at week t
$Urating^a_{i,t}$	Average user rating of software i at week t
$Relevance^a_{i,t}$	The relevance order of software i with its matched CNETD free trial i at week t
$Age^a_{i,t}$	Days since software i has been posted at week t
$Price^a_{i,t}$	Discount price of software i at week t
$Freeship^a_{i,t}$	A dummy variable that measures if software i is eligible for free shipping at week t

Table 2
Summary statistics of key variables.

	Mean	SD	Min.	Max.
CNETD				
$Download^c_{j,t}$	977,617.55	11,296,481.63	0	202,275,000
$Dummyfree^c_{j,t}$	0.46	0.50	0	1
$Uservolume^c_{j,t}$	50.06	264.57	0	3670
$Dummyuser^c_{i,t}$	0.50	0.50	0	1
$Urating^c_{j,t}$	3.21	1.28	1	5
Amazon				
$Rank^a_{i,t}$	13,145.87	11,636.75	1	42,688
$Uservolume^a_{i,t}$	11.98	44.91	0	2086
$Dummyuser^a_{i,t}$	0.56	0.50	0	1
$Urating^a_{i,t}$	3.28	1.14	1	5
$Relevance^a_{i,t}$	21.49	16.97	1	70
$Age^a_{i,t}$	1695.89	1057	0	5090
$Price^a_{i,t}$	100.37	281.41	0.01	10,623.99
$Freeship^a_{i,t}$	0.34	0.47	0	1

including the Amazon software market [6,19]. Following these studies, we took a similar approach and used the negative value of Amazon sales rank with a log transformation ($-LogRank^a_{i,t}$) to approximately measure the log values of actual sales, given the negative linear relationship between them. Naturally, we also used Amazon sales rank to indicate the corresponding product's popularity. Specifically, a high rank, indicated by a smaller value of sales rank, shows high popularity.

To capture the volume of online WOM on Amazon, we followed the literature to adopt the total number of user reviews an Amazon software product has received, $Uservolume^a_{i,t}$ [46]. Prior studies have shown the log-linear relationship between WOM volume and sales; therefore, a natural log transformation was applied to $Uservolume^a_{i,t}$, which resulted in $LogUservolume^a_{i,t}$ [13]. To capture free sampling on CNETD, we used the cumulative counts for which the jth CNETD free trial had been downloaded to measure consumer adoptions of software free sampling. We applied a log transformation on it as $LogDownload^c_{j,t-1}$ in order to convert the value to a comparable magnitude to other variables.

Finally, following Godes and Mayzlin [20] and Liu [29], we adopted a one-week lag in key independent variables that are related with Amazon WOM, Amazon sales rank, and CNETD free sample adoptions. This technique would help better reflect the process of consumers' reaction to Amazon WOM and CNETD free sampling, and their subsequent decision making. The time lag also helps to control for the potential feedback effect from the dependent variable to relevant independent variables. In particular, this helps account for the potential endogeneity of Amazon WOM with respect to the contemporaneous Amazon sales, as prior studies have found a positive feedback mechanism between consumers' participations in online WOM activities and purchase decisions on retail websites [13,20]. Therefore, we only kept the observations within which the relevant Amazon software programs had appeared over at least two consecutive weeks. This process leads to our final sample of 24 weeks of panel data. Table 2 summarizes the statistics of the variables used in this study.

5. Empirical analysis

5.1. Empirical model

We built our model in a Bayesian hierarchical framework as a robust approach to test the interaction effects between free sampling and online WOM [18]. As presented below, the whole model system is composed of two interdependent equations that capture the dynamics between Amazon sales and WOM [14], and four hierarchical equations that explicitly measure the interplay between CENTD free sampling and Amazon WOM. Specifically, the first two equations, AmazonSales and AmazonWOM, are constructed as seemingly unrelated equations to model the sales impact of Amazon WOM and the impact of past sales on Amazon WOM, respectively. AmazonSales equation uses sales rank ($-LogRank^a_{i,t}$) as its dependent variable to infer the sales, given the log-linear relationship between sales rank and sales, and includes volume of past Amazon user reviews as the key independent variable ($LogUservolume^a_{i,t-1}$). AmazonWOM equation, instead, uses $LogUservolume^a_{i,t}$ as a dependent variable and includes $-LogRank^a_{i,t-1}$ as the key independent variable. The adoption of seemingly unrelated equations allows the errors of those two equations to be contemporaneously correlated and thus addresses the concern that omitted factors may exist in both two equations and simultaneously influence Amazon retail sales and volume of Amazon user reviews. In addition, the time lag between the key independent variable and the dependent variable in each equation also excludes the feedback effect caused by the endogeneity of volume of user reviews [13,29]. In those two interdependent equations, we also controlled for product-fixed effect and time-fixed effect to account for any heterogeneity over individual products and over time by using δ_i and δ_t, and ε_i and ε_t, respectively.

AmazonSales equation:

$$\begin{aligned}-LogRank^a_{i,t} = {} & \beta^c_{0,j,t-1} + \beta_1 * LogUservolume^a_{i,t-1} + \beta^c_{2,j,t-1} \\ & * LogUservolume^a_{i,t-1} * \left(1/Relevance^a_{i,t-1}\right) + \beta_3 \\ & * Dummyuser^a_{i,t-1} + \beta_4 * Dummyuser^a_{i,t-1} \\ & * Urating^a_{i,t-1} + \beta_5 * Age^a_{i,t} + \beta_6 * Agesq^a_{i,t} + \beta_7 \\ & * Price^a_{i,t} + \beta_8 * Freeship^a_{i,t} + \delta^a_i + \delta^a_t + \delta^a_{i,t}\end{aligned} \tag{1}$$

AmazonWOM equation:

$$\begin{aligned}LogUservolume^a_{i,t} = {} & \alpha^c_{0,j,t-1} + \alpha_1 * \left(-LogRank^a_{i,t-1}\right) + \alpha^c_{2,j,t-1} \\ & * \left(-LogRank^a_{i,t-1}\right) * \left(1/Relevance^a_{i,t-1}\right) + \alpha_3 \\ & * Dummyuser^a_{i,t-1} + \alpha_4 * Dummyuser^a_{i,t-1} \\ & * Urating^a_{i,t-1} + \alpha_5 * Age^a_{i,t} + \alpha_6 * Agesq^a_{i,t} + \varepsilon^a_i \\ & + \varepsilon^a_t + \varepsilon^a_{i,t}\end{aligned} \tag{2}$$

Equations for the interplay on AmazonSales:

$$\begin{aligned}\beta^c_{0,j,t-1} = {} & \varphi_0 + \varphi_1 * LogDownload^c_{j,t-1} + \varphi_2 * Dummyfree^c_{j,t-1} + \varphi_3 \\ & * LogUservolume^c_{j,t-1} + \varphi_4 * Dummyuser^c_{j,t-1} + \varphi_5 \\ & * Dummyuser^c_{j,t-1} * Urating^c_{j,t-1} + \xi^c_{j,t-1}\end{aligned} \tag{3}$$

$$\beta^c_{2,j,t-1} = \lambda_1 * LogDownload^c_{j,t-1} + \lambda_2 * Dummyfree^c_{j,t-1} + \upsilon^c_{j,t-1} \tag{4}$$

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Equations for the interplay on AmazonWOM:

$$\alpha^c_{0,j,t-1} = \phi_0 + \phi_1 * LogDownload^c_{j,t-1} + \phi_2 * Dummyfree^c_{j,t-1} + \zeta^c_{j,t-1} \tag{5}$$

$$\alpha^c_{2,j,t-1} = \gamma_1 * LogDownload^c_{j,t-1} + \gamma_2 * Dummyfree^c_{j,t-1} + \omega^c_{j,t-1} \tag{6}$$

$$\begin{bmatrix} \varepsilon^a_{i,t} \\ \delta^a_{i,t} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sum^a_{\varepsilon\varepsilon} & \sum^a_{\varepsilon\delta} \\ \sum^a_{\delta\varepsilon} & \sum^a_{\delta\delta} \end{bmatrix} \right) \tag{7}$$

In AmazonSales, we decomposed the sales impact of volume of Amazon past reviews into the main effect, and the interaction effect with CNETD free sampling. As a result, $\beta_1 * LogUservolume^a_{i,t-1}$ was included to capture the former, and $\beta^c_{2,j,t-1} * LogUservolume^a_{i,t-1} * (1 / Relevance^a_{i,t-1})$ was included to measure the latter. In particular, $\beta^c_{2,j,t-1}$ was constructed as a heterogeneous coefficient which is dependent on the *j*th CNETD free trial and further explained by Eq. (4) via a hierarchical structure. Specifically in Eq. (4), to test H1, we included $LogDownload^c_{j,t-1}$ to capture the interplay between free sampling and Amazon WOM on retail sales. H1 suggests a positive interaction effect and thus a positive coefficient on $LogDownload^c_{j,t-1}$ (λ_1). We also included a dummy variable, $Dummyfree^c_{j,t-1}$, as a control variable in Eq. (4) to indicate whether the *j*th CNETD free trial is a freeware product. Free sampling licensing is always a crucial issue in the software industry and has been shown to significantly influence consumer behaviors [9]. The inversed relevance order, $1 / Relevance^a_{i,t-1}$, was included as a multiplier for the interaction effect, on $LogUservolume^a_{i,t-1}$, in AmazonSales to account for our matching process. As described beforehand in data collection, each *i*th Amazon software was 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 the exact commercial version of the *j*th CNETD free trial, we assumed that the interaction between downloads of the *j*th CNETD free trial and user reviews of the *i*th Amazon software should be more significant when the *j*th CNETD free trial and *i*th Amazon are more relevant. Note that closer relevance leads to a smaller value of $Relevance^a_{i,t-1}$.

We are also aware of the widely discussed direct impact of CNETD free sampling on Amazon sales [9,41]. Therefore, we followed the statistical suggestion from the literature that the Bayesian hierarchical model should completely separate the lower level, i.e., CNETD free sampling, from estimating the AmazonSales equation [18,33]. To do so, we constructed a similar hierarchical structure on the intercept term ($\beta^c_{0,j,t-1}$) of the AmazonSales equation. This leads to Eq. (3), which also has CNETD past software download ($LogDownload^c_{j,t-1}$) and free trial license difference ($Dummyfree^c_{j,t-1}$) as two of the independent variables. In addition, we also included the constant term, and three other control variables, volume and valence of CNETD user reviews ($Uservolume^c_{j,t-1}$, $Dummyuser^c_{j,t-1}$, $Dummyuser^c_{j,t-1} * Urating^c_{j,t-1}$), to control for the potential impact of CNETD user reviews on Amazon sales [21].

Following a similar approach, we constructed Eqs. (5) and (6) to test H2a and H2b and H3 respectively. Specifically, Eq. (5) was constructed to model the random intercept term ($\alpha^c_{0,j,t-1}$) in the AmazonWOM equation. Accordingly, the independent variable of CNETD past software download ($LogDownload^c_{j,t-1}$) was included in Eq. (5) to estimate the direct impact of CNETD free sampling on volume of Amazon WOM. A positive coefficient on this term (ϕ_1) would imply H2a and a negative coefficient would, instead, imply H2b. The difference in free trial license ($Dummyfree^c_{j,t-1}$) was again included as a control variable. To test H3, we developed Eq. (6) to explain the random coefficient $\alpha^c_{2,j,t-1}$ on Amazon sales rank, captured by $(-LogRank^a_{i,t-1}) * (1 / Relevance^a_{i,t-1})$, in the AmazonWOM equation. $-LogRank^a_{i,t-1}$ is used to infer Amazon sales and correspondingly product popularity. Therefore, $LogDownload^c_{j,t-1}$ in Eq. (6) measures whether the impact proposed by H2a and H2b, i.e., the impact of CNETD free sampling on Amazon WOM, depends on product popularity. According to H3, we would expect to see a negative coefficient on $LogDownload^c_{j,t-1}$ (γ_1) in this equation. $Dummyfree^c_{j,t-1}$ was also used as a control variable to capture the license difference.

Following previous studies, we also included several control variables in the first two seemingly unrelated equations (AmazonSales and AmazonWOM). Prior studies have shown that valence of user reviews significantly influences consumer purchase choices [10]. Hence, in the AmazonSales equation, we included the information related with valence of Amazon WOM ($Dummyuse^a_{i,t-1}$,$Urating^a_{i,t-1}$). In addition, price effect was controlled for by $price^a_{i,t-1}$. A dummy variable, $Freeship^a_{i,t-1}$, was used to control for the difference in availability of free shipping service among the collected software programs. We also used product age, $Age^a_{i,t-1}$, and the quadratic term of product age, $Agesq^a_{i,t-1}$, to control for product diffusion [14]. Those two terms were thus also included in the AmazonWOM equation. We also included information about the 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. [13]. Overall, by estimating the whole model system, we would be able to empirically investigate the interplay between free sampling and online WOM by particularly monitoring the coefficients of λ_1, φ_1, γ_1 in Eqs. (4), (5), and (6), respectively.

6. Results

We estimated our model system using the Markov Chain Monte Carlo method (MCMC) on the pooled data of seven categories. Specifically, we specified vague normal priors for all unknown parameters. We first used a burn-in of 15,000 draws to characterize the posterior distributions of parameters. Both the history plots and Gelman-Rubin diagnostic showed that MCMC draws have converged to the stationary. Therefore, we used an additional 15,000 MCMC draws to estimate all parameters. Table 3 shows the estimation results by the posterior means and standard deviations.

We first look into Eq. (4) to test H1 regarding the sales effect of the interplay between free sampling and online WOM. The estimation of a significantly positive λ_1 supports H1, which implies that unlike advertisement, free sampling positively interacts with WOM marketing strategy to influence retail sales in the online market. This result helps broaden the application of integrated information response theory to understand the interplay between two marketing strategies in the online market. Free sampling of software programs complements online user-generated WOM to encourage online purchases, which to our best knowledge has not been theorized and empirically tested before. Consumers are more influenced by the high volume of online WOM to make purchases of software programs when the free samples of those products have already been widely adopted on the market. Especially given the nearly zero marginal cost of producing a software free trial, free sampling in the online market seems even more inviting for amplifying the WOM effect.

We also find evidence supporting H2a by a positive ϕ_1 on $LogDownlaod^c_{j,t-1}$ in Eq. (5). CNETD free sampling directly helps generate Amazon user reviews. This impact is quite substantial. Receiving 10% more CNETD free-trial downloads can lead to an increase of 3% in volume of Amazon user reviews, as indicated by ϕ_1. This result answers to the debate we raised earlier in hypothesis development regarding H2a and H2b. Our empirical findings show that consumers' desire to ease the tension caused by their free sampling experiences, overall, dominates their needs for achieving self-enhancement by leaning towards reviewing less frequently sampled products [12,23]. This result expands the territory of the results from Holmes and Lett [24], conducted four decades ago in the offline market, that consumers who have adopted free samples will be more likely share their opinions. Our estimations show that this also occurs in the online market for experience goods; however, the relationship is more intricate, which will be explained below in regard to H3.

We now proceed to discuss the differential effect of free sampling on review volume of products with different popularities. We find that in

Table 3
Estimation results of the interplay between CNETD software free sampling and Amazon user reviews.

		M	SD
AmazonSales equation			
$LogUservolume^{a}_{i,t-1}$ (β_1)		**0.03**	1.25E−4
$Urating^{a}_{i,t-1}$ (β_4)		**0.18**	0.01
$Age^{a}_{i,t}$ (β_6)		**−1.79E−3**	2.01E−5
$Freeship^{a}_{i,t}$ (β_8)		**0.33**	0.01
$Dummyuser^{a}_{i,t-1}$ (β_3)		**0.07**	0.03
$Price^{a}_{i,t}$ (β_5)		**−9.59E−5**	1.20E−5
$Agesq^{a}_{i,t}$ (β_7)		**3.56E−7**	5.14E−9
AmazonWOM equation			
$-LogRank^{a}_{i,t-1}$ (α_1)		**24.72**	0.12
$Urating^{a}_{i,t-1}$ (α_4)		**−3.47**	0.25
$Agesq^{a}_{i,t}$ (α_6)		**−1.17E−5**	2.01E−7
$Dummyuser^{a}_{i,t-1}$ (α_3)		**2.78**	0.95
$Age^{a}_{i,t}$ (α_5)		**0.06**	7.98E−4
Equations for the interplay on AmazonSales			
Eq. (3)	$LogDownload^{c}_{j,t-1}$ (φ_1)	**−0.02**	0.01
	$LogUservolume^{c}_{j,t-1}$ (φ_3)	1.57E−4	6.43E−5
	$Urating^{c}_{j,t-1}$ (φ_5)	−0.02	0.01
	$Dummyfree^{c}_{j,t-1}$ (φ_2)	−2.76E−3	0.04
	$Dummyuser^{c}_{j,t-1}$ (φ_4)	**0.09**	0.03
Eq. (4)	$LogDownload^{c}_{j,t-1}$ (λ_1)	**3.09E−4**	1.02E−4
	$Dummyfree^{c}_{j,t-1}$ (λ_2)	2.24E−3	1.35E−3
Equations for the interplay on AmazonWOM			
Eq. (5)	$LogDownload^{c}_{j,t-1}$ (ϕ_1)	**0.29**	0.05
	$Dummyfree^{c}_{j,t-1}$ (ϕ_2)	0.68	0.37
Eq. (6)	$LogDownload^{c}_{j,t-1}$ (γ_1)	**−0.04**	0.01
	$Dummyfree^{c}_{j,t-1}$ (γ_2)	**0.29**	0.13
Error correlation between AmazonSales equation and AmazonWOM equation		**−0.81**	1.80E−3

Notes: boldface type indicates the significance of estimators, namely the 95% posterior credible interval does not cover zero. The intercepts and fixed effects are not reported yet available upon request.

Eq. (6), the coefficient (γ_1) on total downloads ($LogDownload^{c}_{j,t-1}$) is significantly negative. Since Eq. (6) explains the random coefficient $\alpha^{c}_{2,j,t-1}$ on the negative value of product sales rank in the AmazonWOM equation, the negative value of γ_1 shows that the impact of free sampling on volume of user reviews is more significant for less popular products. Accordingly, H3 is supported. Consumers realize that existing reviews of less popular products are limited in number, as compared to those of popular products. Therefore, they perceive that it is more likely to have others read and value their reviews on those less popular products, due to the lack of sufficient visibility and product information on the market. And thus they would more likely release the tension caused by the high involvement from their free sampling experience. This result supports the finding of Gapol et al. [16] that free sampling may threaten the superstar phenomenon. It also adds to the evidence for the prediction of long tail formation reported in prior papers [1,44]. Free sampling, which has been prevalent in the online market due to its easy access, extensive reach, and low production cost, helps unpopular products to receive user reviews and thus consumer attention.

In addition to testing hypotheses, we also find evidence for the dynamics between volume of Amazon reviews and Amazon sales, which is consistent with prior findings [13]. The positive coefficient on $LogUservolume^{a}_{i,t-1}$ (β_1) in the AmazonSales equation shows a positive impact of volume of past reviews on retail sales. Similarly, in the AmazonWOM equation, the impact of Amazon past sales on the volume of Amazon user reviews is significantly positive, indicated by a positive α_1 on $LogRank^{a}_{i,t-1}$.

We also find that software free trial is shown to have a negative direct impact on Amazon sales, indicated by a negative coefficient on $Logtotaldown^{c}_{j,t-1}$ (φ_1) in Eq. (3). This adds to the debate in the literature over the impact of free sampling on market outcome. Our results suggest that, in the online software market, promoting free sampling directly cannibalizes more demand than it attracts. In addition to the wide reach of the Internet and low marginal cost of software free trials, another reason underlying such a greater demand cannibalization can be the lifetime availability offered by trialware, one particular type of free trial license. Consumers likely found the partial function of trialware to be sufficient and were satisfied, especially given its free price. Nevertheless, this negative effect is very limited in its magnitude. A 10% increase in CNETD free trial downloads can only reduce the sales rank on Amazon by 0.2%. And moreover, this is merely the direct impact of free sampling. Our results above on testing hypotheses, on the contrary, indicate that free sampling can indirectly benefit sales by making firms' WOM marketing strategy more effective as well as encouraging more WOM created by online consumers. The relative magnitude between those two opposite effects of free sampling in the online market may depend on the specific context, which can potentially explain the divergent conclusions of its overall effect in different contexts of the prior studies [2,8,9,11,32,36,40,41].

Finally, we conducted brief robustness checks. We used the *t* distribution to replace the normal prior distribution for all unknown parameters and error terms in the AmazonSales and AmazonWOM equations [17,26]. The *t* distribution can help account for the heavier tail in the distribution of Amazon sales and volume of user reviews, which has been documented by the recent long tail phenomenon [1]. We also tested this model with the *t* prior distribution and our original full model individually in each of two following subsets of our data, as mentioned beforehand in the Section 4.1: one subsample that only included CNETD free trials and their top one matched Amazon products, and the other subsample that only included CNETD free trials and their top five matched Amazon products, respectively. In each test, the estimation results of all coefficients are qualitatively the same, which adds to the robustness of our hypotheses tests. For parsimony, the detailed results are not reported, but they are available upon request.

7. Conclusions, discussion, and limitations

To our best knowledge, this study is the first to examine the interplay between free sampling in digital format and online WOM, two prevalent marketing practices, in the online market. We find that they positively interact with each other in affecting online retail sales. In addition, free sampling in digital format also helps encourage more active online WOM activities. For example, the software program will receive 3% more user reviews on Amazon, if its free trial on CNETD has been downloaded 10% more often. More user reviews lead to better visibility on the market and ultimately greater sales [13,29]. Therefore, free sampling in digital format is shown to benefit the online WOM marketing by amplifying its sales impact and volume. We also find that the interplay between free sampling in digital format and online WOM can contribute to the long tail consumption pattern discussed in the literature [1]. In the online market, the impact of free sampling on volume of WOM is more significant for relatively less popular products.

These results are insightful for online vendors and marketers. First, we recommend applying a free sampling strategy to facilitate WOM marketing in the online market. Specifically, we suggest that online vendors and marketers should view free sampling in digital format and online WOM as two related marketing strategies in the online market. The successful application of a free sampling strategy in online market, implied by extensive consumer adoptions of free samples, can enhance the effectiveness of online WOM marketing in two ways. Unlike the relationship between free sampling and advertising, free sampling in digital format and online WOM won't interfere with each other, but, instead, reinforce each other's sales effect. Therefore, they can be adopted at the same time for greater benefits. Moreover, free sampling in digital format can also help with the implementation of online WOM marketing. Nowadays, vendors and marketers have allocated significant resources to encourage online consumers share their feedback online, by building online reward mechanism to recognize reviewers'

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contribution, giving out monetary incentives for sharing reviews, etc. [42]. Our findings suggest that free sampling in online market is also an effective tool to attract consumers to write reviews online. It is relatively inexpensive to offer, as its marginal production cost is nearly zero and it generally does not incur any cost for being hosted by online platforms. Given those attributes, free sampling in digital format is attractive to serve as a complementary strategy for WOM marketing in the online market.

Our findings also advise vendors and marketers to evaluate the free sampling strategy in the online market in terms of its long-run benefits, in addition to its direct effect on market outcome. Even though free sampling in the online market incurs very low cost, marketers have always been concerned about its potential negative effect on sales due to its cannibalization of demand. This is indeed observed in our empirical analysis; consumers can be satisfied with the free sample and thus lose their need to purchase the commercial version. However, this direct negative effect on sales is quite limited, at least in our online software context. For example, doubling the free trial downloads on CNETD can only reduce sales rank by 2% on Amazon. On the other hand, free sampling in digital format encourages online WOM significantly. Doubling CNETD free trial downloads can increase the volume of Amazon WOM by nearly one-third. Therefore, merely looking at the direct sales effect of free sampling can be misleading in evaluating its online market outcome. Similarly, firms should also incorporate the interaction effect of free sampling in digital format to accurately evaluate the return of their online WOM marketing, if both two strategies have been applied.

In addition, free sampling can be especially appealing to niche products and new products in the online market of experience goods. Those products especially strive to get potential consumers aware of them, provide sufficient product information, and allay consumers' concerns about product quality, as they are unfamiliar and new to most of people in the online market. Free sampling in the online market of experience goods is normally in digital format and therefore costs little. However, it can not only provide product quality information by inviting consumers to try out in person at extremely low cost, but also persuade more consumers to spread the word online about those unpopular/new products after consumption. As a result, it helps those niche and new products to grow in the online market.

Nevertheless, this study has limitations. First, free sampling in the online market as discussed in this paper is constrained to free sampling in digital format whose commercial version normally falls into the category of experience goods. It does not include free sampling in the physical format which takes place at the market of physical goods and/or at a physical location. Unlike in our digital context, customers are not easily aware of others' adoption decisions of free samples in physical format. In addition, when those free samples are consumed at a physical location, e.g. free perfume samples at beauty stores, there is a significant distance between that physical location and the WOM website. Therefore, our results need to be very carefully applied to interpret the practice of offering free samples in the physical format. It would also be interesting to further investigate such practice and re-examine its interplay with online WOM. Second, our data include CNETD free trials and approximately matched software on Amazon. It is a compromised approach to collect data of a sufficiently large size without manually conducting each matching. Although we have tested the model on the full data set and two different subsamples and find qualitatively similar results, it would be beneficial in future research to manually construct a small number of exactly matched free trial and commercial products to re-examine those relationships. Third, we recognize that although CNETD is the leading platform offering software free sampling, some Amazon consumers may still experience free trials on other online platforms before they arrive at Amazon. In future research, it would be interesting to use online consumers' footstep data to investigate the sequence of their download, purchase, and WOM activities. Last but not least, the effect of free sampling found in our research context, i.e. the online software market, can be even more significant in the online market for other experience goods. Software programs have relatively more objective product information, including technology specifications and test performance, than movies and books, the latter of which are heavily influenced by the consumer's individual taste. Therefore, having first-hand experience can be even more needed and trusted for those products, leading to a more significant interplay of free sampling with online WOM.

References

[1] C. Anderson, The Long Tail: Why the Future of Business Is Selling Less of More, Hyperion Press, New York, 2006.
[2] Y. Bakos, E. Brynjolfsson, D. Lichtman, Shared information goods, Journal of Law and Economics 42 (1) (1999) 117–156.
[3] T. Bao, T.S. Chang, Finding disseminators via electronic word of mouth message for effective marketing communications, Decision Support Systems 67 (2014) 21–29.
[4] K. Bawa, R. Shoemaker, The effects of free sample promotions on incremental brand sales, Marketing Science 23 (3) (2004) 345–363.
[5] J. Bughin, J. Doogan, O.J. Vetvik, A new way to measure word-of-mouth marketing, The McKinsey Quarterly (2010) (http://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/a-new-way-to-measure-word-of-mouth-marketing/).
[6] E. Brynjolfsson, Y. Hu, M.D. Smith, Consumer surplus in the digital economy: estimating the value of increased product variety at online booksellers, Management Science 49 (11) (2003) 1580–1596.
[7] E. Brynjolfsson, Y. Hu, M.D. Smith, From niches to riches: the anatomy of the long tail, Sloan Management Review 47 (4) (2006) 67–71.
[8] R.K. Chellappa, S. Shivendu, Managing piracy: pricing and sampling strategies for digital experience goods in vertically segmented markets, Information Systems Research 16 (4) (2005) 400–417.
[9] H.K. Cheng, Y. Liu, Optimal software free trial strategy: the impact of network externalities and consumer uncertainty, Information Systems Research 23 (2) (2012) 488–504.
[10] J.A. Chevalier, D. Mayzlin, The effect of word of mouth on sales: online book reviews, Journal of Marine Science 43 (3) (2006) 345–354.
[11] S. Dewan, J. Ramaprasad, Social media, traditional media, and music sales, MIS Quarterly 38 (1) (2014) 101–121.
[12] E. Dichter, How word-of-mouth advertising works, Harvard Business Review 44 (6) (1966) 147–166.
[13] W. Duan, B. Gu, A.B. Whinston, The dynamics of online word-of-mouth and product sales—an empirical investigation of the movie industry, Journal of Retailing 84 (2) (2008) 233–242.
[14] W. Duan, B. Gu, A.B. Whinston, Informational cascades and software adoption on the Internet: an empirical investigation, MIS Quarterly 33 (1) (2009) 23–48.
[15] J.M. Gallaugher, Y.-M. Wang, Understanding network effects in software markets: evidence from web server pricing, MIS Quarterly 26 (4) (2002) 303–327.
[16] R.D. Gapol, S. Bhattacharjee, G.L. Sanders, Do artists benefit from online music sharing? Journal of Business 79 (3) (2006) 1503–1533.
[17] A. Gelman, D.B. Rubin, Inference from iterative simulation using multiple sequences, Statistical Science 7 (4) (1992) 457–472.
[18] A. Ghose, A. Goldfard, S.P. Han, How is the mobile Internet different? Search costs and local activities, Information Systems Research 24 (3) (2013) 613–631.
[19] A. Ghose, A. Sundararajan, Software versioning and quality degradation? An Exploratory Study of the Evidence, CEDER Working Paper No. CeDER-05-20, New York University, New York, 2005.
[20] D. Godes, D. Mayzlin, Using online conversation to study word of mouth communications, Marketing Science 23 (4) (2004) 545–560.
[21] B. Gu, J. Park, P. Konana, The impact of external word-of-mouth sources on retailer sales of high-involvement products, Information Systems Research 23 (1) (2012) 182–196.
[22] E. Haruvy, A. Prasad, Optimal freeware quality in the presence of network externalities: an evolutionary game theoretical approach, Journal of Evolutionary Economics 11 (2) (2001) 231–248.
[23] T. Hennig-Thurau, K.P. Gwinner, G. Walsh, D.D. Gremler, Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the Internet? Journal of Interactive Marketing 18 (1) (2004) 38–52.
[24] J.H. Holmes, J.D. Lett, Product sampling and word of mouth, Journal of Advertising Research 17 (5) (1977) 35–41.
[25] D.S. Kempf, R.E. Smith, Consumer processing of product trial and the influence of prior advertising: a structural modeling approach, Journal of Marketing Research 35 (3) (1998) 325–338.
[26] K.L. Lange, R.J.A. Little, J.M. Taylor, Robust statistical modeling using the t distribution, Journal of the American Statistical Association 84 (408) (1989) 881–896.
[27] Y.-J. Lee, Y. Tan, Effects of different types of free trials and ratings in sampling of consumer software: an empirical study, Journal of Management Information Systems 30 (3) (2013) 213–246.
[28] Z. Lin, An empirical investigation of user and system recommendations in e-commerce, Decision Support Systems 68 (2014) 111–124.
[29] Y. Liu, Word of mouth for movies: its dynamics and impact on box office revenue, Journal of Marketing 70 (3) (2006) 74–89.
[30] L.J. Marks, M.A. Kamins, The use of product sampling and advertising: effects of sequence of exposure and degree of advertising claim exaggeration on consumers'

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belief strength, belief confidence, and attitudes, Journal of Marketing Research 25 (3) (1988) 266–281.
[31] Nielsen, Consumer Trust in Online, Social and Mobile Advertising Grows, 2012 (http://www.nielsen.com/us/en/insights/news/2012/consumer-trust-in-online-social-and-mobile-advertising-grows.html Accessed 16.03.24).
[32] F. Oberholtzer-Gee, K. Strumpf, The effect of file sharing on record sales: an empirical analysis, Journal of Political Economy 115 (1) (2007) 1–42.
[33] P.E. Rossi, G.M. Allenby, R. McCulloch, Bayesian Statistics and Marketing, Wiley, Chichester, England, 2005.
[34] H. Row, Influencing the Influencers: How Online Advertising and Media Impact Word of Mouth, 2006 (http://www.digitaltrainingacademy.com/research/click2.pdf Accessed 16.03.24).
[35] H. Rui, Y. Liu, A.B. Whinston, Whose and what chatter matters? The effect of tweets on movie sales, Decision Support Systems 55 (4) (2013) 863–870.
[36] S. Sarkar, Z. Jiang, Speed matters: the role of free software offer in software diffusion, Journal of Management Information Systems 26 (3) (2009) 207–240.
[37] R.E. Smith, Integrating information from advertising and trial: processes and effects on consumer response to product information, Journal of Marketing Research 30 (2) (1993) 204–219.
[38] R.E. Smith, W.R. Swinyard, Information response models: an integrated approach, Journal of Marketing 46 (1) (1982) 81–93.
[39] R.E. Smith, W.R. Swinyard, Attitude-behavior consistency: the impact of product trial versus advertising, Journal of Marketing Research 20 (3) (1983) 257–267.
[40] H.R. Varian, Versioning Information Goods, 1997 (http://people.ischool.berkeley.edu/~hal/Papers/version.pdf Accessed 16.03.24).
[41] C. Wang, X. Zhang, Sampling of information goods, Decision Support Systems 48 (1) (2009) 14–22.
[42] WOMMA, The State of Word of Mouth Marketing: A Survey of Marketers, 2014 (http://womma.org/the-state-of-womm-2014/ Accessed 16.03.24).
[43] A.A. Wright, J.G. Lynch Jr., Communication effects of advertising versus direct experience when both search and experience attributes are present, Journal of Consumer Research 21 (4) (1995) 708–718.
[44] W. Zhou, W. Duan, Online user reviews, product variety, and the long tail: an empirical investigation on online software downloads, Electronic Commerce Research and Applications 11 (3) (2012) 275–289.
[45] W. Zhou, W. Duan, Do professional reviews affect online user choices through user reviews?: an empirical study, Journal of Management Information Systems 33 (1) (2016) 202–228.
[46] F. Zhu, X. Zhang, Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics, Journal of Marketing 74 (2) (2010) 133–148.

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