An Investigation of Free Product Sampling and Rating Bias in E-Commerce

Research-in-Progress

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Abstract

Free product sampling has increasingly become a popular promotional strategy, and served as a new mechanism of product review generation in e-commerce. We empirically analyze how a product's engagement in free product sampling affects the product's review rating, and also examine important contingent factors of product pricing and product popularity. Using a rich data set from Taobao.com and multiple identification strategies and estimation methods, we find that engaging in free product sampling increases product rating by 1.1%. We argue that it is consumers' reciprocal behavior of giving higher ratings as a return to retailers' beneficial actions that causes rating bias. We further find that the bias would be larger with higher original price, but smaller with higher price discount and higher product popularity. Our empirical findings provide important contributions to the literature on product sampling and word-of-mouth, and offer critical managerial implications to online retailers, rating system designers, and consumers.

Keywords: Product sampling, product trial, rating bias, product review, word-of-mouth, electronic commerce, econometric analysis

Introduction

Electronic commerce (e-commerce) sites are one of the common contexts in which product reviews are generated. Typically, textual reviews and numerical ratings of a product can be generated after consumers' purchase and usage of the product, which has become the most dominant mechanism of product review generation in e-commerce. Recently, free product sampling has become an additional mechanism. Free product sampling is a popular promotional strategy that has long been employed by firms to boast product sales (Schultz et al. 1998). This strategy was first used for physical goods in the offline context (Bawa and Shoemaker 2004; Heiman et al. 2001; Marks and Kamins 1988), and then information goods (e.g., software) in the online context (Chellappa and Shivendu 2005; Cheng and Liu 2012; Lee and Tan 2013; Niculescu and Wu 2014), and recently physical goods in e-commerce. Many e-commerce firms (e.g., Taobao.com, JD.com and YHD.com)[1] have increasingly launched their own platforms for product sampling promotions. Typically, e-commerce retailers will provide a certain amount of free samples of a sampling product[2] during the product sampling promotion. Consumers can then apply for a free sample, and the successful applicants can receive it. After consumers try the product, as a return, they need to write a review for the product to be integrated with the existing product reviews.

Prior research on free product sampling has documented the existence of ***reciprocity*** in consumer behavior (Bawa and Shoemaker 2004). When consumers are given a product for free, they may have feelings of obligation to behave more friendly in response to retailers' beneficial actions (Cialdini 1993; Fehr and Gächter 2000). Given that providing review ratings is a typical way for consumers to respond to retailers in e-commerce, we thus conjecture that, in the context of e-commerce product sampling, consumers who receive a free product are likely to behave more friendly by providing a higher rating for the product when writing the review, which may eventually result in deviations in the overall product rating from its "true" level. Consequently, the usefulness and value of product ratings could be undermined. Moreover, prior literature has also argued that the extent of reciprocity is contingent upon the imputed value of the benefit received (Gouldner 1960), which suggests that rating deviations are likely to depend on product characteristics, such as pricing and popularity, that could signal the value of a product. As free product sampling is getting more and more popular in e-commerce, deviations in product ratings are likely to have significant consequences. Therefore, we are interested in understanding how free sampling promotion of a product affects the product's rating, and the roles of important contingent factors, including: (1) product pricing, and (2) product popularity.

We answer these questions using a rich panel data set from the largest e-commerce website in China, Taobao.com, on 2,524 products from January 2016 to March 2016. Empirically identifying the impact of product sampling on product rating is challenging due to the potential endogeneity issue of sampling promotion of a product. We thus address the endogeneity using multiple identification strategies.

We find robust evidence that conducting free sampling promotion for a product increases the product's rating. Specifically, our estimate shows that, on average, a product's engagement in free product sampling increases the product's rating by 1.1%. Our additional investigations of the contingent factors find that the impact of free sampling on product rating would be stronger with higher product original price, but weaker with higher price discount and higher product popularity.

This research contributes to the literature in several ways. First, we enrich and extend the product sampling literature by studying free product sampling of physical goods in e-commerce. Second, we contribute to the word-of-mouth (WOM) literature by empirically documenting the existence of rating bias due to free product sampling. Third, this research adds insights to the literature on product sampling and WOM by studying and validating several important contingent factors. The notable findings from this research also offer important implications for managerial practices.

[1] Taobao product sampling center: http://try.taobao.com
JD product sampling center: http://try.jd.com
YHD product sampling center: http://try.yhd.com
[2] In this study, sampling product refers to the product that engages in free product sampling promotion.

Literature Review

Free product sampling or trial, as an effective marketing strategy, has attracted considerable research effort (Biswas et al. 2010; Biswas et al. 2014; Nowlis and Shiv 2005; Shiv and Nowlis 2004; Wadhwa et al. 2008). However, existing studies have only focused either on product sampling of physical goods in the offline context (e.g., Bawa and Shoemaker 2004; Heiman et al. 2001; Marks and Kamins 1988) or that of information goods in the online context (e.g., Chellappa and Shivendu 2005; Cheng and Liu 2012; Lee and Tan 2013; Niculescu and Wu 2014). There has been little research on product sampling of physical goods in e-commerce. Furthermore, the product sampling literature has not examined the potential relationship between product sampling and bias in product reviews or WOM.

While research on the connection between product sampling and WOM has been absent, extensive research effort has been devoted to examining the role of WOM (Chen and Xie 2008; Dellarocas 2003; Godes and Mayzlin 2009; Li and Hitt 2010; Mayzlin 2006; Mudambi and Schuff 2010). For instance, prior studies have widely documented that WOM has critical impacts on consumer decision making (Goh et al. 2013; Pavlou and Dimoka 2006), product sales (Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Clemons et al. 2006; Duan et al. 2008; Forman et al. 2008; Gu et al. 2012; Lin 2014; Liu 2006; Zhu and Zhang 2010), and firm performance (Antweiler and Frank 2004; Chen et al. 2014; Das and Chen 2007; Tirunillai and Tellis 2012).

Given the influential role of WOM, its value largely depends on how effective it can deliver true information regarding consumers' product evaluations. However unfortunately, the WOM literature has documented some factors and mechanisms that could cause biases in WOM, or more specifically, product rating (e.g., Godes and Silva 2012; Li and Hitt 2008; Lin and Heng 2015; Wu and Huberman 2008). For instance, Li and Hitt (2008) analyzed book review data from Amazon to show the existence of self-selection bias due to the fact that early and later consumers have different preferences about the quality of a product, and readers of early reviews may not successfully correct for these differences when making purchase decisions. Moreover, Wu and Huberman (2008) uncovered that later reviewers may be affected by previous reviews to have a trend-following tendency. Godes and Silva (2012) explored the dynamic aspects of product ratings and argued that later consumers have decreasing ability to assess similarity with past reviewers and then will have more purchase errors. Interestingly, through the lens of expectation-confirmation theory (Oliver 1977; Oliver 1980), Lin and Heng (2015) also analyzed the dynamic aspects of product ratings and discovered that extremely high ratings are more likely to attract negative reviews subsequently due to consumers' higher perceived impact of reviewing, which may result in an under-reporting bias.

In addition to these dynamic aspects, some studies also reported social factors that could lead to biases in WOM (e.g., Moe and Trusov 2011; Schlosser 2005; Wang et al. 2016). For instance, Schlosser (2005) demonstrated that users may adjust their attitudes in the presence of social concerns (e.g., self-presentational concerns). Moe and Trusov (2011) identified that there are substantial social dynamics in a rating environment, and consumers' ratings can be affected by others' ratings. Recently, Wang et al. (2016) studied the impacts of online friend relationship on product ratings and uncovered that rating similarity between friends is significantly higher after the formation of the friend relationships. The authors claimed that observational learning and peer pressure should be the underlying influencing mechanisms.

Data

We obtain data from the largest e-commerce website in China, Taobao.com. Taobao has about 500 million registered users, more than 60 million daily active users, and more than 800 million products (Taobao 2016). Taobao is an independent e-commerce platform that facilitates the transactions between individual retailers/stores and consumers. That is, there are numerous online stores on Taobao, and each store itself can decide what products to sell in the store. Thus, it is possible that a product can be sold in multiple stores at the same time. This thus provides us a convenient setting to observe an identical pair of products with one engaging in product sampling but not the other. Thus, we would be able to construct a "control group" of non-sampling products for identification purposes. Typically, each product has an independent webpage, displaying product information such as product title, original list price, price discount, product review, past sales, after-sales service, etc.

Taobao has started providing product sampling services by launching the largest e-commerce product sampling center in China in 2011, i.e., Taobao sampling center (http://try.taobao.com). A typical sampling promotion campaign follows these five steps. First, a retailer submits a sampling campaign application to the sampling center regarding her product. Second, the sampling center approves the application and places the target product in the "Coming Soon" section, including information such as product title, product list price, sampling size, and promotion starting date. This step is commonly done several days or even weeks before the start of the actual promotion. Third, the sampling center moves the target product to the "Ongoing" section when the promotion starts for Taobao users to apply for a free sample of the target product. This step lasts for seven days. Fourth, the sampling center select the successful applicants and deliver a free sample to each of them. Fifth, after these successful applicants receive and try the free sample, they are required to write a review for the product. These reviews will be integrated with the existing product reviews on the product webpage in the corresponding store.

We design a Python-based crawler for data collection. We record products that appear in the "Coming Soon" section, which are sampling products but have not yet engaged in sampling promotion. For each of these sampling products on the same day, we manually identify a certain number of stores selling this identical, but non-sampling, product. The number of identical non-sampling comparison products mostly ranging from 1 to 3, which depends on the availability on Taobao. The crawler will be executed on a daily basis to go through the webpages of all the recorded products (including sampling[3] and non-sampling products) to collect all observable product information. Overall, our final unbalanced panel-level data set includes 120,820 observations for 2,524 products (i.e., 26,259 observations for 536 sampling products and 94,561 observations for 1,988 non-sampling products). Based on Taobao's categorization, all the products are grouped into nine categories, including: (1) apparels, (2) household items, (3) home appliances, (4) digital products, (5) skincare products, (6) makeups and perfumes, (7) maternal and child products, (8) health food, and (9) other products.

Empirical Model and Analysis

We construct our model variables at the product-day level. Let subscript *i* denote each individual product, and subscript *t* denote each day. Our *independent variable*, SP_{it}, is a binary indicator for product sampling engagement. That is, $SP_{it} = 1$ if product *i* has engaged in product sampling on day *t*, zero otherwise. Our *dependent variable*, RR_{it}, indicates product *i*'s review rating on day *t*. Finally, the *control variables* are gathered from those identified in prior literature and from the available information in our data set. Specifically, we include control variables at the individual product, product category, and time unit levels: (1) product original list price[4] (LP_{it}), (2) product price discount[5] (DC_{it}), (3) product review volume (RV_{it}), (4) product past sales[6] (PS_{it}), (5) free delivery[7] (FD_{it}), (6) after-sales service[8] (AS_{it}), (7) payment mode[9] (PM_{it}), (8) product category dummies (C_i), and (9) time dummies at the daily level (T_t).

To address our first research question, we model the influence of $SP_{i,t-1}$ on RR_{it}, to allow for a lagged effect from free product sampling to consumers' provision of review ratings, and also to avoid potential simultaneity issues. The panel-level linear model is specified in Equation (1):

$$\begin{aligned} RR_{it} = {} & \beta_1 SP_{i,t-1} + \beta_2 LP_{it} + \beta_3 DC_{it} + \beta_4 RV_{it} + \beta_5 PS_{it} \\ & + \beta_6 FD_{it} + \beta_7 AS_{it} + \beta_8 PM_{it} + C_i\gamma + T_t\omega + \alpha_i + \varepsilon_{it} \end{aligned} \tag{1}$$

where βs, γ, and ω are the model coefficients, α_i captures unobserved product-specific effect, and ε_{it} indicates the residual random error term.

[3] Noteworthy, all the sampling products in our data set have engaged in only one sampling promotion.
[4] This indicates the original price of product *i* on day *t*.
[5] This indicates the difference between the original price and the actual transaction price of product *i* on day *t*.
[6] This indicates the sales quantity of product *i* during the past month prior to day *t*.
[7] This is a binary variable indicating whether the retailer provides free delivery for product *i* on day *t*, with one indicating free delivery and zero otherwise.
[8] This indicates the total number of different types of after-sales services (e.g., warranty) provided by the retailer to consumers for product *i* on day *t*.
[9] This indicates the total number of different modes of payment (e.g., Alipay, credit card) provided by the retailer to consumers for product *i* on day *t*.

We first estimate a fixed effects (FE) model of product review rating (*RR*) on the independent variable of product sampling engagement, *SP*, with all the control variables included. As reported in Table 1, Column (1), the estimated coefficient of *SP*, 0.046 (±0.007), is positive and statistically significant, suggesting a positive relationship with *RR*. In addition to the FE model, we further estimate a RE model of *RR* on all the independent and control variables and summarize the results in Table 1, Column (2). Consistently, the estimated coefficient of *SP*, 0.045 (±0.007), is almost identical to that of the FE estimate. The Hausman test result (χ^2 = 106.11, p = 0.0055) shows that RE estimates would be inconsistent as the unobserved product-specific effect α_i is correlated with the explanatory variables. Thus, we consider the results of the FE model in Column (1) as our preferred baseline results. Based on this baseline model, we further estimate and report the elasticity of product rating, *RR*, with respect to product sampling engagement, *SP*. As indicated in Column (1), the estimated elasticity suggests that a product's engagement in product sampling promotion increases the product's review rating by 1.1%.

Although the result in Table 1, Column (1), shows that *SP* indeed has a positive relationship with *RR*, this analysis may be subject to endogeneity issue as *SP* could be endogenous due to reasons such as the omission of relevant factors and selection issue of products that engage in free sampling. We thus apply our identification strategies to address the potential endogeneity concern.

As discussed above, our unique setting allows us to simultaneously observe the "treatment" group (i.e., sampling products) and "control" group (i.e., identical but non-sampling products). Moreover, for each product in the "treatment" group, we are also able to observe the period before (i.e., before the "Ongoing" period starts) and after (i.e., after the "Ongoing" period starts) a product engages in product sampling. Thus, we can exploit differences across products' sampling decision and across timing differences in sampling starting dates to use a difference-in-differences (DID) model estimation approach. Based on our "treatment" group and constructed "control" group, we estimate the DID model in Equation (2):

$$\begin{aligned} RR_{it} &= \beta_1 IS\_SP_i * AF\_SP_{it} + \beta_2 IS\_SP_i + \beta_3 AF\_SP_{it} \\ &+ \beta_4 LP_{it} + \beta_5 DC_{it} + \beta_6 RV_{it} + \beta_7 PS_{it} \\ &+ \beta_8 FD_{it} + \beta_9 AS_{it} + \beta_{10} PM_{it} + C_i\gamma + T_t\omega + \alpha_i + \varepsilon_{it} \end{aligned} \tag{2}$$

where IS_SP_i is a binary indicator for product sampling engagement decision, with one indicating sampling product and zero otherwise. AF_SP_{it} is a binary indicator for the post sampling period of product i and i's comparison product on day t. AF_SP_{it} equals one for the day when product i's sampling promotion starts and all the subsequent days, and equals zero otherwise. Based on the Equation (2), β_1 is the DID estimator which represents the impact of sampling promotion on product rating.

Our data set has the "treatment" group of 536 sampling products, and 1,988 identical non-sampling products. Thus, we can make use of the 1,988 non-sampling products to properly construct the "control" group. Our strategy to construct our "control" group is to employ the Propensity Score Matching (PSM) technique (Heckman et al. 1998; Rosenbaum and Rubin 1983). We use a set of observable variables for PSM matching, including: (1) product inventory, IN_{it}, the available quantity of product i for sale on day t, (2) product webpage bookmark, BM_{it}, the number of webpage bookmarks of product i on day t, (3) product description, DS_{it}, the length (by character count) of descriptions (e.g., highlights of any unique attributes) of product i on day t, and (4) product category dummies (C_i). We expect that a product's sampling engagement decision, IS_SP_i, to be related to these factors due to the following reasons. First, if the retailer intends to conduct sampling promotion for a product, then the retailer may expect an increase in product exposure and accordingly prepare a larger *IN*. Second, *BM* may indicate the extent to which consumers are interested in the product, which could serve as a criterion for the retailer's choice of product to engage in sampling promotion. Third, *DS* implies the retailer's marketing effort to introduce the product to the public, and thus is likely to correlate with the retailer's decision of conducting free sampling promotion for the product which is another marketing strategy. Lastly, we expect retailers on Taobao to have preferences for choosing certain product categories for sampling promotion, which could be captured by product category dummies *C*.

Based on the above factors, we perform PSM matching with the one-to-one nearest-neighbor matching (without replacement) algorithm, which is recognized as the optimal matching method in the literature (Austin 2010), to construct the "control" group. We then estimate the DID model and summarize the results in Table 1, Column (3). Similarly, the coefficient of *IS_SP* * *AF_SP*, 0.036 (±0.018), remains positive and significant, suggesting the positive impact of sampling promotion on product rating.

In sum, after addressing the potential endogeneity issue based on the above strategies, we find that sampling promotion has a positive impact on product rating. In other words, our estimation results show that product sampling promotion can indeed lead to bias (inflated) in product rating.

Table 1. Result: Free product sampling engagement

Variable	(1) FE	(2) RE	(3) DID PSM
SP	0.046***	0.045***	
	(0.007)	(0.007)	
IS_SP * *AF_SP*			0.036**
			(0.018)
AF_SP			0.063***
			(0.014)
LP	-0.036*	-0.027*	-0.050*
	(0.020)	(0.016)	(0.025)
DC	0.015**	0.016**	0.056***
	(0.006)	(0.006)	(0.010)
RV	-0.029***	-0.004*	-0.019***
	(0.004)	(0.002)	(0.004)
PS	-0.006**	-0.013***	-0.008***
	(0.002)	(0.002)	(0.002)
FD	-0.034	-0.017	-0.094**
	(0.032)	(0.031)	(0.040)
AS	-0.044***	-0.038**	-0.025
	(0.016)	(0.015)	(0.020)
PM	0.049***	0.050***	0.061***
	(0.013)	(0.013)	(0.017)
Constant	4.336***	4.439***	4.570***
	(0.056)	(0.114)	(0.073)
Elasticity of *SP*	0.011***	0.011***	
	(0.002)	(0.002)	
Category dummies	-included-	-included-	-included-
Time dummies	-included-	-included-	-included-
Number of sampling products	536	536	536
Number of non-sampling products	1,988	1,988	536
Number of products	2,524	2,524	1,072
Number of observations	117,798	117,798	52,379
Hausman test	χ^2 = 106.11, p = 0.0055		
R^2	0.0032	0.0133	0.0006

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The binary indicator for product sampling engagement decision, *IS_SP*, is included during model estimations but omitted due to its collinearity with *AF_SP* and *IS_SP* * *AF_SP*.

Contingent Factors: Product Pricing and Product Popularity

Our identification strategies and model estimations have found robust evidence that product sampling engagement will positively increase product rating, and thus lead to bias in product rating. After addressing our first research question, we next further explore potential contingent factors which may moderate the identified relationship between product sampling engagement and product rating. For ease of reference, Table 2, Column (1), presents the baseline results from Table 1, Column (1).

First, we expect product pricing factors in terms of original list price (*LP*) and price discount (*DC*) to exert some moderating effects. As discussed above, reciprocity may occur when consumers receive a product for free and thus feel obligated to behave friendly (Bawa and Shoemaker 2004; Cialdini 1993; Fehr and Gächter 2000). We thus argue that if the product is originally more expensive (i.e., higher *LP*), which implies the higher value of the product, consumers who receive the product for free may perceive retailers' actions to be more beneficial and generous. Consequently, consumers may behave even more friendly by giving a much higher rating. In contrast, a larger price discount (i.e., higher *DC*) implies that consumers now can purchase and enjoy the product at a lower cost. Hence, consumers may perceive less benefit from free product sampling, and perceive retailers' actions to be less beneficial and generous. As a result, consumers may feel less obligated to behave friendly to retailers, and the rating bias might be less salient.

Second, we also expect that product popularity may moderate the relationship between product sampling engagement and product rating. That is, higher popularity of a product implies the higher level of consumer preference for the product. Thus, a more popular product obtained through free product sampling is more likely to increase consumers' perceived value and benefit received from retailers. However, a more popular product usually has a higher level of awareness among consumers. Retailers are likely to offer a larger number of the product to consumers through free product sampling given retailers' expectation of the higher consumer awareness and interest. Thus, more consumers are expected to give a rating after their sampling of the product. As such, a larger volume of ratings is more likely to reduce the rating bias as it is harder for the sampling product to receive consistently higher rating as a result of consumers' consistent reciprocal action. Moreover, given that more consumers are expected to give a rating after the sampling, consumers may face less pressure to give a higher rating to show their reciprocity, as compared to the case with only one or several consumers that are expected to give a rating after the sampling and thus consumers have more pressure to behave friendly as a return to retailers. Theoretically, the moderating effect of product popularity becomes complicated and equivocal.

To empirically analyze these moderating effects, we first use product list price, *LP*, and price discount, *DC*, as the pricing moderators. We construct and include the interaction terms of *SP* * *LP* and *SP* * *DC* in our model estimation. As shown in Table 2, Column (2), the estimate of *SP* * *LP* is positive and significant, whereas the estimate of *SP* * *DC* is negative and significant. These results thus indicate that the impact of *SP* indeed depends on product pricing factors. The findings show that higher product list price may enhance the impact of product sampling engagement on product rating, whereas higher price discount weakens it. These findings are consistent with our expectations. As to the moderating effect of product popularity, we use product review volume, *RV*, which has been widely recognized as an indicator for product popularity in prior WOM research (Forman et al. 2008; Li and Hitt 2008). Similarly, we construct and include the interaction term of *SP* * *RV* in our model estimation. The negative and significant estimate of *SP* * *RV* in Table 2, Column (3), shows that product popularity indeed moderates the impact of *SP* on *RR*. That is, higher product popularity instead weakens the impact of product sampling engagement on product rating. Lastly, we simultaneously include these three interaction terms for estimations and find similar results in Table 2, Column (4).

Table 2. Result: Product pricing and popularity

Variable	(1) Baseline	(2) Product pricing	(3) Product popularity	(4) Product pricing & popularity
SP	0.046***	0.026***	0.051***	0.031***
	(0.007)	(0.008)	(0.007)	(0.008)
SP * *LP*		0.042***		0.041***
		(0.006)		(0.006)
SP * *DC*		-0.032***		-0.031***
		(0.007)		(0.007)
SP * *RV*			-0.003***	-0.002***
			(0.001)	(0.001)
Constant	4.336***	4.348***	4.324***	4.336***
	(0.056)	(0.056)	(0.056)	(0.056)
Main effects	-included-	-included-	-included-	-included-
Control variables	-included-	-included-	-included-	-included-
Number of sampling products	536	536	536	536
Number of non-sampling products	1,988	1,988	1,988	1,988
Number of products	2,524	2,524	2,524	2,524
Number of observations	117,798	117,798	117,798	117,798
R^2	0.0032	0.0031	0.0030	0.0030

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Conclusion

Our research findings have the following contributions. First, our study has discovered that engaging in free product sampling will increase product rating. In other words, product sampling will lead to rating bias. Past WOM research has reported several factors and mechanisms that may lead to biases in WOM, such as self-selection issues (Li and Hitt 2008), trend-following tendency (Wu and Huberman 2008), dynamic factors (Godes and Silva 2012; Lin and Heng 2015), and social factors (Moe and Trusov 2011; Wang et al. 2016). Our study thus contributes to the WOM literature by identifying a new source of WOM bias, i.e., free product sampling. This also contributes to past product sampling literature by revealing a new role of product sampling, i.e., one of the causes of WOM biases. Additionally, we further contribute by documenting the important contingent factors of product pricing and product popularity which would moderate this bias-generating process.

Second, this research offers important practical insights to online retailers. Our findings show that if a product engages in free product sampling promotion, its product rating would increase. Thus, if online retailers intend to promote the sales of a product, they could choose to conduct product sampling promotion for the product to influence its rating, and to indirectly influence product sales, as past WOM literature has widely documented that increased rating may lead to increased sales (Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Clemons et al. 2006). Particularly, they could choose products with higher original price, lower price discount, and lower product popularity to conduct product sampling promotions to increase product ratings more easily.

Third, this study provides guidance to e-commerce platform operators regarding the design of rating systems. The value of a rating system largely relies on its truthfulness in reflecting consumers' product evaluations (Wang et al. 2016). Since our research findings suggest that product sampling will lead to rating bias, which may undermine the truthfulness of product ratings, rating system designers should be aware of this issue. Designers are advised to develop solutions to help consumers correct the bias. For instance, they could add a label on product webpages to highlight whether a product has engaged in product sampling promotion. By providing additional information, designers could help consumers make better purchase decisions.

Finally, we also offer suggestions to consumers. Consumers have always relied on product ratings as an important information source for their purchase decision making (Chen and Xie 2008; Chevalier and Mayzlin 2006; Duan et al. 2008). However, as we have identified that product sampling could lead to rating biases, consumers should be cautious about ratings of products engaging in free sampling, especially products with higher original list price, lower price discount, and lower popularity. Specifically, when consumers read and evaluate product ratings, they should identify whether a product has engaged in product sampling promotion, and to correct the bias accordingly based on the size of bias quantified in this study, in order to reduce purchase errors due to rating biases (Godes and Silva 2012).

Although this research has highlighted several notable findings and contributions, we acknowledge some limitations. First, although we have provided some discussions on the possible explanations for the impact of free product sampling on product rating, our study did not develop an in-depth theoretical framework to discuss the mechanisms of rating bias generations. Second, our empirical analysis is based on an observational data set. Although we have attempted to address the potential endogeneity issue, we may not have fully controlled for all potential sources of endogeneity bias.

This study can be extended in several ways in future research. First, our empirical analysis is based on an observational data set from an e-commerce website, and thus is limited in terms of research questions that could be investigated based on the availability of our data set. Thus, future research could conduct randomized trials or field experimentations to examine other interesting questions such as how to design the implementations of a free product sampling promotion or product review policies, such that the bias could be eliminated or at least alleviated. Second, due to data limitations, we were not able to observe daily product sales to further examine how rating bias affects product sales. Thus, future research could consider investigating this issue to better understand the roles of product sampling.

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