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Speaking for "Free": Word of Mouth in Free- and Paid-Product Settings

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Abstract

This research examines drivers of consumer word of mouth (WOM) in free-product settings, revealing fundamental differences with traditional, paid-product settings. The authors build and investigate a theoretical model that highlights two unique characteristics of free products (reciprocity motivation and diminished adoption risk) and considers their implications for WOM sharing. Results of a retrospective survey, two controlled experiments, and an analysis of more than 5,000 mobile apps at Google Play and Apple's App Store reveal that consumers are generally more likely to share their opinions of free products than paid products, because of feelings of reciprocity toward the producer. However, this difference is reduced when prior consumer WOM is low in volume and highly disperse, signaling greater adoption risk. These findings contribute to nascent understanding of free-product marketing while offering new insights for catalyzing consumer WOM.

Keywords

free pricing, online reviews, social influence, reciprocity, word of mouth

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Contemporary marketers are witnessing economic and technological transformations that have altered traditional notions of value exchange. A prominent example is the dramatic increase in marketing of "free" products (Bryce, Dyer, and Hatch 2011; Lambrecht and Misra 2017). This trend has been especially evident in markets for digital and information goods. The vast majority of mobile apps are available at no cost (Jones 2013), and the standard in many digital categories is a "freemium" pricing model, which charges only for advanced features or services.

Much of the scholarly interest in free-product pricing has focused on marketplace dynamics and strategic considerations underlying the viability of a zero-price model (Foubert and Gijsbrechts 2016; Kumar 2014; Pauwels and Weiss 2008). Other research has documented psychological anomalies that arise when consumers evaluate free products (Nicolau 2012; Palmeira and Srivastava 2013; Shampanier, Mazar, and Ariely 2007). We expand on this trend by considering a previously neglected topic: the unique drivers of consumer word of mouth (WOM) in free-product settings. Our topic is consequential both theoretically and pragmatically. For firms offering free products (which may lack resources for traditional marketing), WOM is often a primary communication channel.

We investigate two related questions. First, are consumers more or less likely to share WOM for free (vs. paid) products? Second, how and why do sharing motivations differ across the two settings? To address these questions, we build a framework offering two distinct pathways by which free pricing has implications for sharing. The first pathway involves reciprocity, which compels consumers to "give back" to producers of products received at no monetary cost. The second pathway involves perception of adoption risk, which compels consumers to help potential adopters of costly products. To distinguish the two pathways, we incorporate the dynamics of WOM: specifically, we argue that the volume and dispersion of existing WOM should influence perceptions of adoption risk, but not the desire to reciprocate.

We investigate our framework using multiple methodologies: a retrospective survey, two experiments (involving both hypothetical and actual product experiences), and an empirical examination of archival data. Consistent with our theorizing, findings reveal that consumers of free products are generally

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more likely to share their opinions than consumers of paid products, but that this difference is reduced when existing WOM is low in volume and highly disperse. Additional process evidence supports the presence of distinct mediating pathways.

By providing evidence of a substantial role for "free" in facilitating WOM, our research contributes to a nascent literature on the viability, implementation, and consequences of zero-price strategies (Appel, Libai, and Muller 2015; Cheng and Liu 2012; Datta, Foubert, and Van Heerde 2015; Gill, Sridhar, and Grewal 2017; Oh, Animesh, and Pinsonneault 2016). In addition, our exploration of WOM volume and dispersion supplements recent interest regarding WOM dynamics (Lee, Hosanagar, and Tan 2015; Moe and Schweidel 2012). Moreover, we emphasize the roles of specific psychological drivers in shaping these dynamics and how they differ across paid- and free-product settings. Supplementing prior literature portraying WOM as self-serving behavior (e.g., De Angelis et al. 2012), we highlight WOM as a means of serving both producers and other consumers. In doing so, we respond to Berger's (2014, p. 597) call for researchers to "examine factors that encourage people to think more about others."

Conceptual Background

The Pervasive Impact of "Free"

Providing products for "free" is a component of various contemporary pricing strategies (tiered pricing, "freemium" pricing, complementary pricing, etc.). For present purposes, we define a "free" product as one that can be acquired without monetary cost, regardless of the underlying pricing model.[1] However, we acknowledge that consumers may construe "free" in various ways that may or may not include nonmonetary costs, opportunity costs, potential future costs, and so on (Study 3 addresses this issue further).

Psychologists have long known that individuals exhibit unique affective, cognitive, and behavioral responses when objects of value are received without expectation of remuneration. Seminal research by Isen and colleagues demonstrated that unexpected gifts elicit more positive mood, enhanced evaluations of unrelated stimuli, more variety-seeking behavior, and so on (e.g., Isen et al. 1978). Within consumer settings, a wide body of evidence reveals substantial and systematic differences in reactions to paid and free products. Framing a product as "free" can evoke powerful, positive affective responses that influence subsequent evaluations, such that free products are perceived as much more desirable than alternatives of even negligible cost (Shampanier, Mazar, and Ariely 2007). "Free" offers are less likely than "low-price" or "discounted" offers to negatively affect product evaluations or lower reference prices (Chandran and Morwitz 2006; Palmeira and Srivastava 2013). Free-trial promotions enhance sales both by accelerating repeat purchase and by reaching new buyers (Bawa and Shoemaker 2004). In the next sections, we consider an additional, previously neglected benefit of free pricing, by which customers may be more likely to share product-related WOM.

Motivation to Share WOM for Free and Paid Products

A growing literature has explored the diverse motivations underlying consumer WOM (see Berger 2014 for a review). Much of this literature focuses on impression management, showing that to portray a favorable self-image, consumers are more likely to share WOM about interesting products (Berger and Schwartz 2011), WOM that is positive (De Angelis et al. 2012; Wojnicki and Godes 2008), and WOM that is useful to recipients (Moore 2015). Other motivations include emotional regulation (e.g., complaining to reduce negative affect; Hennig-Thurau et al. 2004) and social bonding (e.g., sharing as a means of forming relationships; Chen 2017). We build on these insights to distinguish sharing motivations for free and paid products.

Our framework addresses the following situation: having recently adopted and consumed a free or paid product, a consumer is deciding whether to share her opinions with others. We make the simplifying assumption that most product users (including the one in question) are at least moderately satisfied with their experience. Although this assumption is undeniably restrictive, it is consistent with evidence that the vast majority of online reviews are positive (Hu, Zhang, and Pavlou 2009). Moreover, the value of motivating WOM is highest when consumers are satisfied. (In the general discussion, we consider implications of negative experiences.)

Free products are unique from their paid counterparts in a variety of aspects likely to influence WOM sharing. In the next subsections, we suggest that two of these aspects are especially relevant: (1) heightened reciprocity toward the producer and (2) the perception of lower product adoption risk. These two aspects form the two distinct pathways of our framework.

Reciprocity: Helping Producers Through WOM

The principle of reciprocity captures the notion that "one good turn deserves another." Abundant interdisciplinary research has demonstrated that this principle is broadly endorsed as a norm for social interaction. In general, individuals who receive benefits from others show a strong tendency to return the favor, especially when the received benefits are perceived as valuable (Cialdini et al. 1975; Gouldner 1960; Hoppner and Griffith 2011). In some cases, the need to reciprocate can induce seemingly irrational behavior—for example, complying with requests of greater value than the benefits received (Regan 1971). Downstream effects of reciprocity are observable even in consequential, high-involvement decisions: in one example, provision of small cash gifts to commercial bank customers resulted in larger deposit balances, higher

[1] Whether "free" products truly exist is a source of intense debate (e.g., Evans 2011), and we remain agnostic on this issue (see the "General Discussion" section). Per our definition, a product is considered "free" as long as the buyer is ignorant or insensitive to monetary costs directly associated with the exchange.

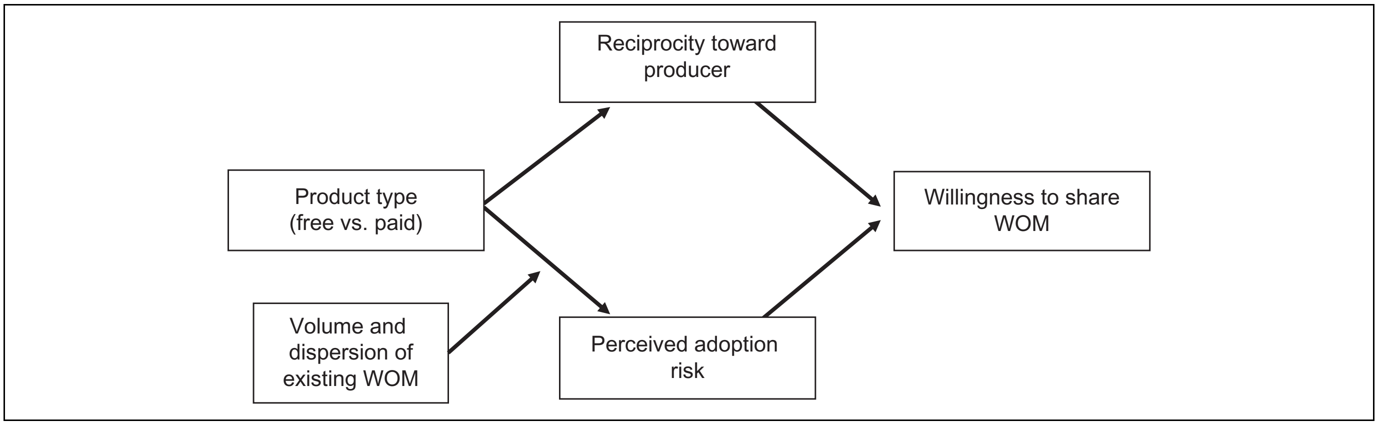

Figure 1. Mechanisms that drive sharing.

survey response rates, and greater satisfaction (Haisley and Loewenstein 2011).

By definition, consumers of free products receive benefits without providing direct (monetary) compensation to the producers of those products. However, it need not be the case that they feel compelled to reciprocate. Modern consumers are often familiar with free or freemium pricing strategies, and they may assume that firms using such strategies extract other value to be profitable. Similarly, consumers may assume that they have already "given back"—for example, by providing attention, exposing themselves to firm messaging, beginning a relationship with the brand, and so on (Newman 2015). Compared with monetary payment, however, such alternative means of remuneration are nebulous, complex, and far removed from the transaction and consumption experience. Thus, we argue that consumers will tend to disregard such means if they are not made explicitly salient. Consistent with this argument, pain of payment appears to decline dramatically as the payment process becomes less conspicuous (Thomas, Desai, and Seenivasan 2011).

To the extent that consumers of free products perceive meaningful benefits (i.e., their consumption experience is satisfactory), the preceding logic suggests that they will be motivated to seek ways to reciprocate. In theory, reciprocation could take various forms (e.g., allowing use of personal information; Schumann, Wangenheim, and Groene 2014). However, in many free-product settings (and especially digital categories), one of the most readily available forms of reciprocation is the transmission of positive WOM regarding the product or producer. By sharing their own experience and opinions, satisfied customers not only endorse a product to other potential customers but also encourage producers to "keep up the good work." In many cases, WOM also provides producers with valuable customer feedback regarding product, usage, or consumer characteristics.

These arguments underlie the first pathway in our framework, which is illustrated in the top half of Figure 1. Consumers of free products (but not paid products) will be motivated to "return the favor" they have received from producers, and they will share their experience with others as a means of doing so. Our mediational hypothesis is as follows:

> H_1: Consumers are more likely to provide WOM for free products than paid products as a result of enhanced reciprocity toward the producer.

Adoption Risk: Helping Other Consumers Through WOM

Like their paid counterparts, free products often necessitate a variety of nonmonetary costs (inventory, maintenance, disposal, etc.). Nonetheless, both intuition and existing evidence suggest that such nonmonetary costs are not generally salient, and consumers typically perceive lower risk in the decision to adopt free products (Aydinli, Bertini, and Lambrecht 2014). Along similar lines, consumers who have incurred no monetary cost are less likely to experience disappointment or regret, even if their experience is unsatisfactory (Simonson 1992).

The desire to help others make informed product decisions is one of the primary motivations for sharing product WOM (Kronrod and Danziger 2013; Moore 2015). Logically, however, the perceived value of a "more informed decision" depends on the extent to which that decision is consequential (i.e., "Does it matter if they choose incorrectly?"). Thus, the lower risk associated with free products has important consequences for sharing: even if potential contributors recognize that sharing will benefit others making a product decision, they may discount the benefit because the decision does not seem consequential. This logic forms the basis for the second pathway in our framework, illustrated in the bottom half of Figure 1.

To help identify and distinguish the contrasting forces of reciprocity (which benefits free products) and adoption risk (which benefits paid products), we incorporate WOM dynamics—the manner in which exposure to existing WOM affects subsequent WOM transmission (Lee, Hosanagar, and Tan 2015; Moe and Schweidel 2012). Given the conspicuous nature of existing WOM, it is reasonable to assume that consumers often use it as an input to their own sharing decision. We focus on two characteristics of existing WOM: volume, which captures the magnitude of prior product-related WOM already available, and dispersion, which captures the extent to which reported consumer evaluations of a product differ from one another. Formally, we define existing WOM volume and dispersion (respectively) as the quantity and standard deviation of product ratings assigned by prior reviewers. At most review platforms, both these characteristics are prominently displayed in either graphical or numeric form.

Both the volume and dispersion of existing WOM provide signals of risk to product adoption. Low (vs. high) volume indicates that less information is available on which to base an adoption decision, and high (vs. low) dispersion indicates that the available information is more conflicted; in both cases, therefore, the perceived risk of a negative outcome should be enhanced. Importantly, however, these signals are most relevant in the case of paid products, for which the "cost" of adoption is more salient (see the previous discussion). In the case of free products, adoption risk should be perceived as low overall and should be relatively unaffected by existing WOM.

Combining these ideas completes the second pathway of our framework. Consumers of paid products (but not free products) will recognize an opportunity to help other consumers mitigate adoption risk by providing WOM. However, they will perceive this opportunity to be greatest when the WOM already available to other consumers is insufficient and conflicting. Formally,

> H_{2a}: Consumers are more likely to provide WOM for paid products than free products as a result of increased product adoption risk.
>
> H_{2b}: The magnitude of this effect is strongest when the volume of existing WOM is low and the dispersion of existing WOM is high.

The "net effect" of free- vs. paid-product pricing on WOM depends on the relative strength of the two pathways. Consistent with prior evidence for powerful and widespread reciprocity effects, it is reasonable to expect that the reciprocity pathway will often dominate the risk pathway. However, the relative strength of the two pathways should become more balanced at high levels of perceived adoption risk. Stated formally,

> H_3: Consumers are more likely to provide WOM for free products than paid products, but the difference is attenuated when the volume of existing WOM is low and the dispersion of existing WOM is high.

In the following sections, we describe four studies conducted to investigate our hypotheses. The product category in all studies was web-based or mobile apps. Beyond the rapid growth of this category in recent years, other properties make it ideal for investigation: (1) both free and paid pricing strategies are common, (2) app developers are heavily reliant on WOM for marketing communications, and (3) app customers actively spread product-related WOM among peers, other users, and popular review platforms.

Dependent measures in the studies include both offline WOM (i.e., verbal recommendation) and online WOM (i.e., review posting). Study 1 investigates the reciprocity pathway by measuring the recalled WOM behavior of actual app users. Study 2 explores both pathways in a controlled experiment with a realistic payment and consumption experience. Study 3 replicates and extends the prior study with a scenario-based survey design. Study 4 examines archival data from real-world app platforms to test our predictions in a natural environment.

Study 1: Retrospective Recall—Free Versus Paid Apps

Our first study utilized a retrospective recall design to investigate whether free apps trigger greater reciprocity and WOM transmission. The target category in the study was mobile gaming apps.

Method

Experimental procedure. One hundred ninety-six U.S. residents were recruited from Amazon Mechanical Turk (MTurk) and compensated for their time (design and sample considerations were similar to Zhang, Feick, and Mittal [2014]). Participants were first asked whether they could identify a free game app that they had played recently on a mobile device and been satisfied with overall. Next, they were asked whether they could identify a paid game app meeting the same criteria. Thirty-four participants who could not answer both questions were disqualified. The rest were randomly assigned to one of two between-subject conditions (product type: free vs. paid). Depending on condition, participants were asked to provide the name of either the free or paid app that they had identified before, and then complete the dependent measures described next. They also completed demographic items and a condition manipulation check, which asked how much money they had spent on the app.

WOM behavior. Using a binary (yes/no) measure, participants reported whether they had "recommended the app to someone else" in the past.

WOM likelihood. We adapted the likelihood and satisfaction measures from Zhang, Feick, and Mittal (2014). Participants rated the likelihood that they would recommend the game app to someone else in the near future, using three seven-point items ("certain not to recommend/certain to recommend," "very unlikely to recommend/very likely to recommend," and "probably will not recommend/probably will recommend"). We averaged the three items.[2]

[2] For participants who reported recommending the app in the past, a value of seven was assigned. All following reported effects remain similar in magnitude and significance when stated values are used instead.

Satisfaction. The satisfaction measure was included both to ensure that recalled experiences were positive and to control for potential differences in satisfaction. Participants evaluated their experience with the app using two seven-point items ("very negative/very positive" and "extremely unsatisfied/extremely satisfied"), and we averaged the two items.

Intention to reciprocate. To capture intention to reciprocate, we adapted two items from Zhang and Epley (2009). Participants rated the extent to which they were "grateful toward the app developers" (1 = "not at all grateful," and 7 = "very grateful") and would "like to thank the developers" (1 = "not at all," and 7 = "a great deal"). Responses to the two items were averaged.

Results

Six participants failed the condition manipulation check, resulting in a usable sample of 156 participants (mean age = 33 years; 44% female). Satisfying our positivity assumption, participants recalled their experiences with the apps as positive (M = 6.19, SD = .95). Satisfaction was somewhat higher for free than paid apps (M = 6.37 vs. M = 6.02; $F(1, 154) = 5.51$, $p < .05$).

WOM behavior and likelihood. We first examined the retrospective measure of WOM behavior. In the free condition, 76% of participants recalled having recommended the app to someone else, but in the paid condition, only 66% of participants recalled doing so ($\chi^2(1) = 2.22$, $p < .10$). We next examined the prospective measure of WOM likelihood. Participants in the free condition reported a significantly greater likelihood of recommending the app to someone else than participants in the paid condition (M = 6.50 vs. M = 5.92; $F(1, 154) = 7.67$, $p < .01$).

Intention to reciprocate. Participants in the free condition reported significantly greater intention to reciprocate to the app developer than participants in the paid condition (M = 5.42 vs. M = 4.98; $F(1, 154) = 3.85$, $p = .05$). To examine the reciprocity pathway formally, we conducted a bootstrapping mediation analysis with repeated extraction of 5,000 samples (Hayes 2013, Model 4). The model included past WOM transmission behavior as the dependent variable, product type as the independent variable (0 = free, 1 = paid), and intention to reciprocate and satisfaction as mediating variables. Results revealed an indirect, negative effect of product type on past WOM transmission behavior through intention to reciprocate (B = −.29, SE = .15, 95% CI = [−.66, −.05]). As predicted by H_1, participants were less likely to have transmitted WOM for paid apps owing to lower reciprocity intention. Results also revealed a negative, indirect effect of product type through satisfaction (B = −.16, SE = .11, 95% CI = [−.46, −.01]), such that participants were less likely to have transmitted WOM for paid apps owing to a less positive experience. Using WOM likelihood as the dependent variable, results again revealed a negative indirect effect of product type through intention to reciprocate (B = −.08, SE = .05, 95% CI = [−.22, −.01]).

Discussion

Study 1 produced initial evidence for the proposed reciprocity pathway. Despite vast heterogeneity in apps and experiences, participants who recalled a free (vs. paid) app were more likely to have recommended that app to others and were more likely to do so in the future. These differences appeared to be driven in part by greater reciprocity toward the developer,

The retrospective design of Study 1 is subject to several valid concerns, including the possibility that pricing affected memory of past WOM behavior rather than actual behavior. Addressing these concerns, Study 2 provided a "real-time" consumption experience and examined actual decisions to share WOM. The study also investigated the second pathway in our model, by which free pricing may inhibit WOM as a result of perceptions of lower adoption risk.

Study 2: Experiment—Decision to Share WOM for a Web App

The focal product of our second study was a web-based photo editing app created specifically for the study (see Web Appendix A). The inclusion of a "real" product ensured that participants could actually experience the product before deciding whether to post a review, and it also allowed for a realistic manipulation of product type.

Method

Experimental procedure. Three hundred eighty-eight U.S. residents were recruited from MTurk and compensated for their time. Participants were randomly assigned to one of eight conditions in a 2 (product type: free vs. paid) × 2 (WOM volume: low vs. high) × 2 (WOM dispersion: low vs. high) between-subjects design.

The cover story informed participants that they would be using two different apps—one free and one paid—in a random order.[3] Participants were asked to imagine that they were planning a business trip to China with a colleague, who needed a visa photo that met the requirements of the Chinese Embassy. Participants had volunteered to help create the photo for their colleague, using a web-based photo editing app provided by the experimenters.

To manipulate product type, participants learned either that the photo app was free of charge or that it cost $.50 per photo created. To ensure that participants in the paid condition actually "experienced" the act of paying (Rick, Cryder, and Loewenstein 2008), they were told that $.50 would be deducted from their study compensation ($2), and they were reminded of this charge immediately before accessing the app. The app was located on a separate website and accessed by clicking a hyperlink: after undergoing a brief training session, participants

[3] Providing this information ensured that participants in both free and paid conditions would expect the same total compensation. At the end of the study, participants were informed that there was no "second app" to evaluate.

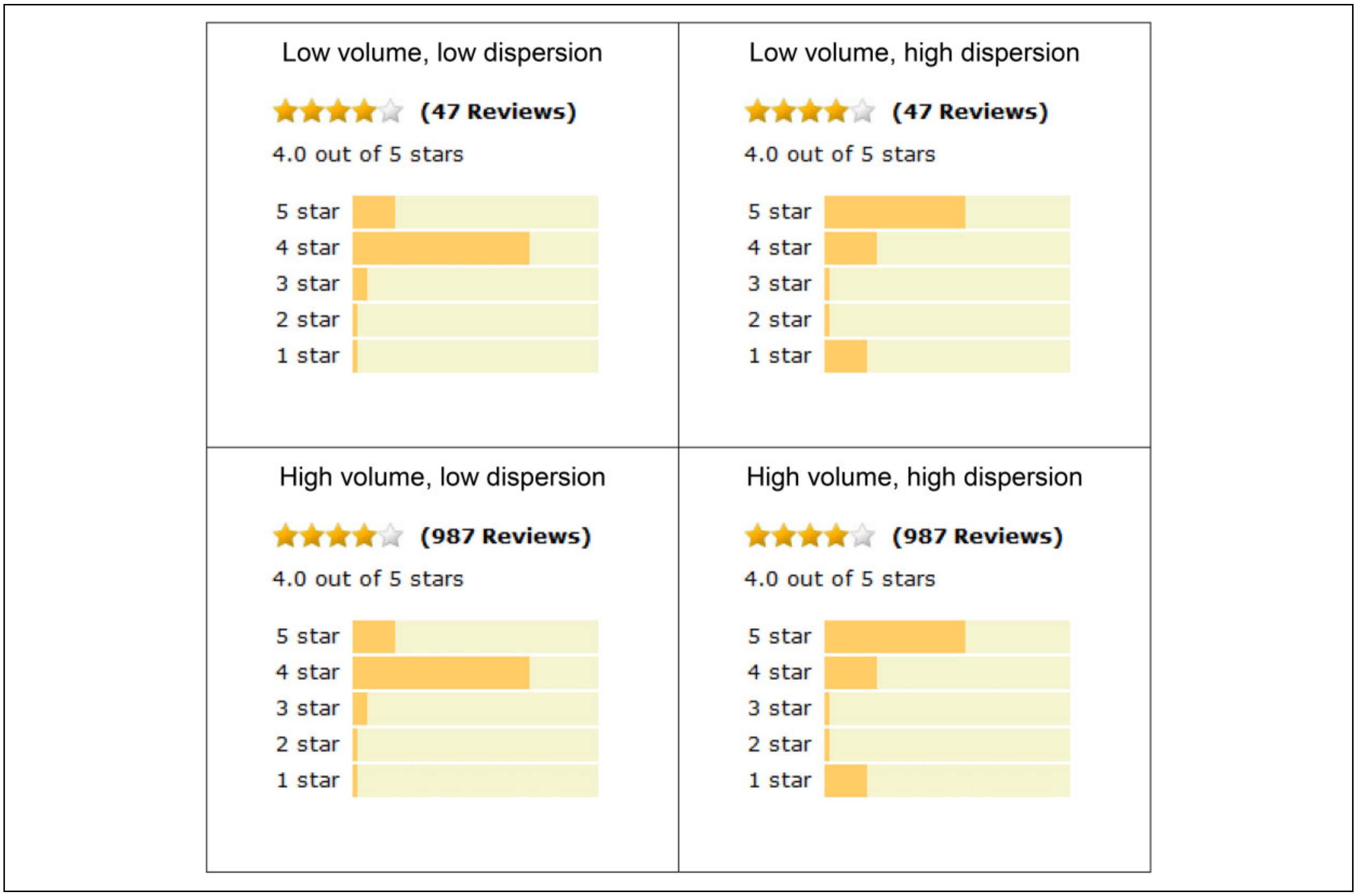

Figure 2. WOM distributions for Study 2.

followed a step-by-step process to create the photo for their colleague.

Immediately after they finished using the photo app, participants were shown a message "from the app developers" requesting that they post a review of their experience on a popular review forum. The following screen presented a summary of existing reviews at the forum, in which the volume and dispersion manipulations were embedded (see Figure 2). Participants in the low- (high-) volume condition saw that the app had received 47 (987) reviews, and the text noted that "not many (many) people have posted reviews." Dispersion was manipulated in the form of graphical ratings distributions (similar to He and Bond [2015]). The means of the two distributions were identical (four stars out of five), but their standard deviations differed substantially ($SD = .71$ vs. $SD = 1.49$ for low and high dispersion, respectively). Accompanying text noted that the app had "received very similar (very diverse) reviews from previous users: the ratings given by most users did not differ very much (some users gave very high ratings, and other users gave very low ratings)." The manipulations were validated through a separate pretest, described in Web Appendix B.

Participants stated their decision whether to post a review for the photo app, and afterward they responded to the process measures described next. Finally, they completed a demographic questionnaire including measures for age, gender, frequency of review posting, prior use of similar apps, and attention checks (Oppenheimer, Meyvis, and Davidenko 2009).

Intention to reciprocate. Participants completed two items identical to those in Study 1.

Perceived adoption risk. Participants rated their agreement with two statements (1 = "strongly disagree," and 5 = "strongly agree"): (1) "Potential users will be uncertain about the usefulness of the app," and (2) "For potential users, whether or not to adopt the app is a difficult decision." Responses to the two items were averaged.

Attitude toward the app. To ensure that participants held positive and similar opinions of the app, they completed three seven-point items ("not at all good/very good," "not at all effective/very effective," and "not at all useful/very useful"). Responses were averaged.

Results

Thirty-four participants either failed to open the photo app, did not complete the study, missed more than one attention check, or incorrectly recalled the product type; excluding them left a

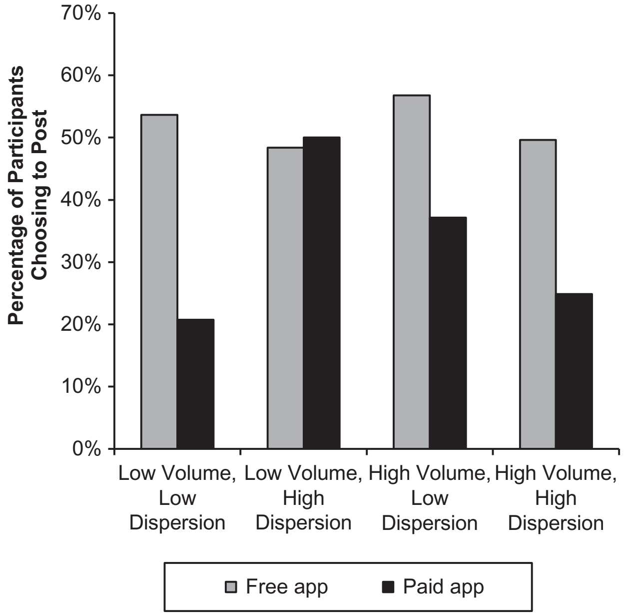

Figure 3. Study 2: Effects of WOM volume, WOM dispersion, and product type on choosing whether to post a review.

sample of 354 participants (mean age = 37 years; 47% female). Fewer than 5% of participants reported prior use of similar apps, and the results remain similar if those participants are excluded. Attitude ratings indicated that participants were satisfied with the app overall (M = 5.65, SD = 1.07). Forty-eight percent of participants indicated that they "never" or "rarely" posted consumer reviews.

Posting decision. Figure 3 illustrates the proportion of participants in each condition who agreed to post a review. We examined decision to post with a binary logistic regression including product type, WOM volume, WOM dispersion, and their interactions, controlling for frequency of review posting.[4] Analyses revealed a main effect of product type ($\chi^2(1) = 8.79$, $p < .01$), such that a larger proportion of participants chose to post a review when the app was free than paid (52% vs. 33%).[5] Most importantly, analyses also revealed a significant product type × volume × dispersion interaction effect ($\chi^2(1) = 3.86$, $p < .05$).

To explore the interaction, we conducted separate follow-up contrasts at each level of existing WOM volume. When volume was high, results revealed only a main effect of product type (Z = 2.94, $p < .01$), such that posting was more likely when the app was free than paid. When existing volume was low, however, results revealed a significant product type × dispersion interaction (Z = 2.30, $p < .05$) whose pattern was consistent with hypothesis 2b: when dispersion was also low, posting was more likely when the app was free than paid (54% vs. 21%; Z = 3.24, $p < .01$), but when dispersion was high, the difference nearly disappeared (48% vs. 50%; Z = −.14, $p > .30$).

Intention to reciprocate. An analysis of variance (ANOVA) including the three treatment variables and their interactions revealed a significant main effect of product type (F(1, 346) = 24.30, $p < .001$), such that intention to reciprocate was higher when the app was free rather than paid (M = 4.86 vs. M = 4.02; F(1, 346) = 24.30, $p < .001$). To investigate the reciprocity pathway formally, we conducted a mediation analysis similar to that described in Study 1. Consistent with hypotheses, results revealed an indirect, negative effect of product type on posting choice through the intention to reciprocate (B = −.34, SE = .18, 95% CI = [−.80, −.07]). Results did not support a mediating role for attitude toward the app (B = −.15, SE = .13, 95% CI = [−.44, .07]).

Perceived adoption risk. According to the second pathway of our framework, charging for a product increases the perceived risk of adoption when existing WOM signals uncertainty. An ANOVA revealed a marginal main effect of product type (F(1, 346) = 3.23, $p = .07$), a significant main effect of volume (F(1, 346) = 5.23, $p < .05$), and a directional effect of dispersion (F(1, 346) = 1.26, $p = .26$). Most important, results revealed a significant product type × volume × dispersion interaction (F(1, 346) = 8.31, $p < .01$). Consistent with our hypotheses, the effect of product type on perceived risk was most pronounced at a combination of low volume and high dispersion ($M_{free} = 2.74$ vs. $M_{paid} = 3.21$; F(1, 346) = 6.41, $p < .05$).

To explore the pathway formally, we conducted a moderated mediation analysis using bootstrapping with repeated extraction of 5,000 samples (Hayes 2013, Model 11). The analysis included product type as the independent variable (0 = free, 1 = paid), perceived adoption risk as the mediator, volume (0 = low, 1 = high) and dispersion (0 = low, 1 = high) as moderators, and posting choice as the dependent variable, controlling for frequency of review posting. As predicted, results revealed an indirect, positive effect of product type on posting choice through perceived adoption risk, which was moderated by the volume × dispersion interaction (B = −.28, SE = .19, 95% CI = [−.79, −.01]). Follow-up analyses indicated that the indirect effect was reliable at a combination of low volume and high dispersion (B = .12, SE = .09, 95% CI = [.01, .36]), but not at any other volume × dispersion combination (Bs = −.04 to .09; all 95% CIs include zero).

[4] When frequency of review posting is not controlled for, the product type × volume × dispersion interaction becomes marginal ($p < .10$). The mediation effect of intention to reciprocate (B = −.41, SE = .23, 95% CI = [−.93, −.01]) and the moderated mediation effect of perceived adoption risk (B = −.36, SE = .21, 95% CI = [−.91, −.06]) are supported.

[5] In an exploratory analysis, we examined the text reviews written by the participants who chose to post, using the Linguistic Inquiry and Word Count (Pennebaker et al. 2015). Among notable findings, reviews in the free condition contained marginally more positive emotional words than those in the paid condition (M = 12.10 vs. M = 9.57; F(1, 144) = 3.15, $p = .08$) and indicated directionally greater effort (M = 26.72 vs. M = 22.82; F(1, 144) = 1.80, $p = .18$).

Discussion

Using an experimental design and a realistic consumption setting, Study 2 demonstrated distinct implications of free pricing for WOM, involving both reciprocity and perceptions of adoption risk. Reflecting the reciprocity route, participants were more likely overall to post a review when the product was free. Reflecting the perceived risk route, this effect was virtually eliminated when prior WOM was limited in volume and highly disperse.

Participants in Study 2 did not view information about prior WOM until they had already experienced the app. Often, however, prior WOM is encountered before a product decision (and may influence that decision). Therefore, we conducted the follow-up study reported in Web Appendix C. Participants in the follow-up study chose between two different apps based on their prior WOM distributions, experienced the app, and decided whether to post a review. They also provided open-ended comments about the app developer. Findings were consistent with those of the main study, though evidence for the mediating pathways was not conclusive. Moreover, exploratory text analysis of open-ended comments (described in the Appendix) suggested that reciprocity motivation was stronger in the free condition.

Study 3: Experiment—Intention to Share WOM for a Mobile App

Our third study was designed to replicate Study 2 in a more controlled setting while extending the investigation to other forms of free-product pricing. "Free" products often come with qualifications that create value for providers (e.g., advertising, time or usage limitations, paid upgrades or accessories). The more salient the qualifications, the more likely consumers should be to view the exchange as costly. In terms of our two pathways, therefore, qualifications should *reduce* motivation to share WOM as a means of reciprocation but *increase* motivation to share WOM as a means of reducing others' adoption risk. To explore these ideas, we examined three common pricing models that differ in the extent to which qualifications are salient: free, free + ads, and paid (described next).

Study 3 was entirely scenario-based, ensuring that all participants shared an identical consumption "experience" with the target app. Participants were told that after an ongoing and satisfactory experience, they had been asked by the app developers to provide a review. As in Study 2, participants viewed a summary of existing reviews (in which volume and dispersion were manipulated) before making their decision. Stimuli are provided in Web Appendix D.

Method

Experimental procedure. Seven hundred seventy-eight U.S. residents were recruited from MTurk and compensated for their time. Participants were randomly assigned to 1 of 12 conditions in a 3 (product type: free vs. free + ads vs. paid) $\times$ 2 (WOM volume: low vs. high) $\times$ 2 (WOM dispersion: low vs. high) between-subjects design. The cover story asked participants to imagine that they recently downloaded a mobile app, "HealthyU," which helps users monitor their diet and exercise while maintaining a healthy lifestyle (the description was adapted from Batch et al. [2014]). All participants were told that they had downloaded a "basic" version of the app, which could be upgraded to an "advanced" version for a fee. To manipulate product type, participants learned that the basic version was free of charge and ad-free (free), free of charge with sponsored advertising (free + ads), or $2.99 and ad-free (paid).

The scenario explained to participants that after two months of generally positive experiences with the app, participants had received a pop-up message from the developers, requesting that they post a review. Participants then viewed a summary of existing reviews, in which the four volume $\times$ dispersion conditions were represented by graphical distributions identical to those in Study 2. Participants reported their intention to post a review and responded to process measures described next. At the end of the study, they rated the realism of the scenario (1 = "not realistic at all," and 7 = "extremely realistic"), and they completed attention checks and demographic questions similar to those in Study 2.

Intention to post. Participants rated both how likely (1 = "not very likely," and 7 = "very likely") and how motivated (1 = "not very motivated," and 7 = "very motivated") they would be to "post a star rating and a text review" at the review forum. Responses to the items were averaged.

Intention to reciprocate, perceived adoption risk, attitude toward the app. Participants completed measures identical to those in Study 2.

Self-serving motivation. A plausible alternative to our reciprocity mechanism is that consumers spread WOM for free products to ensure that the products continue to be available, continue to be updated, and so on. To capture such "self-serving" motivation, we included two five-point Likert-type items measuring the extent to which it was in participants' best interest to help the developers and the extent to which they would do so "to benefit myself." Responses to the items were averaged.

Chance of survival. On the one hand, consumers may feel that the effort of sharing WOM is only worthwhile for products that are likely to "survive" in the marketplace. On the other hand, consumers may see greater value in sharing WOM when they perceive survival to be in jeopardy. To explore both possibilities, we asked participants how likely it was that the app would "be successful for a long period of time" (1 = "not likely at all," and 5 = "extremely likely").

Results

Ninety-five participants did not complete the study, failed more than one attention check, or incorrectly recalled their product

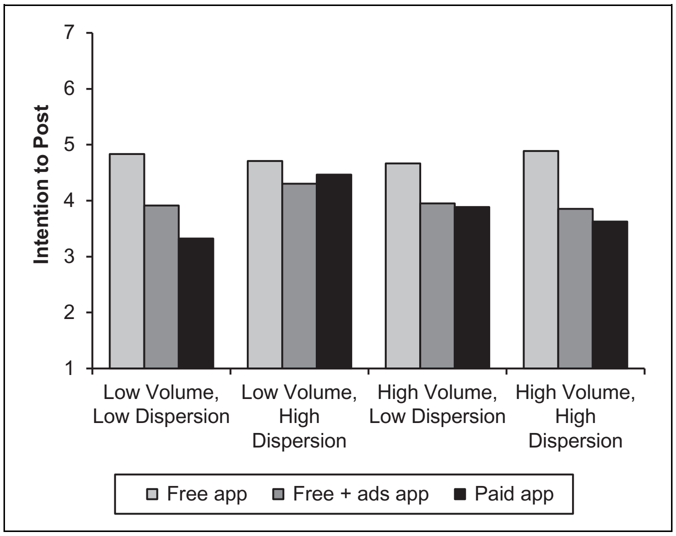

Figure 4. Study 3: Effects of WOM volume, WOM dispersion, and product type on intention to post a review.

Notes: Product type was manipulated as follows: the app was either free to download and ad-free (free), free to download with sponsored advertising (free + ads), or cost $2.99 to download and was ad-free (paid).

type condition; their exclusion left a sample of 683 participants (mean age = 35 years; 53% female). On average, participants deemed the scenario realistic (M = 5.73, SD = 1.21) and had a positive attitude toward the app (M = 5.64, SD = 1.02). Fifty-eight percent of participants indicated that they had used a similar app in the past.[6]

Intention to post. Figure 4 depicts mean intention to post by condition. As predicted, an ANOVA revealed a significant main effect of product type (F(2, 671) = 16.53, $p < .001$). Participants were more willing to post a review when the app was free than paid (M = 4.77 vs. M = 3.82; F(1, 671) = 28.83, $p < .001$). Intention to post in the new, free + ads condition (M = 4.01) was significantly lower than that in the free condition (F(1, 671) = 19.59, $p < .001$), but only directionally higher than that in the paid condition (F(1, 671) = 1.06, $p = .30$).

Analyses also revealed a significant product type × volume × dispersion interaction (F(2, 671) = 3.07, $p < .05$), whose pattern was consistent with predictions. At high existing volume, results indicated only a main effect of product type (F(2, 671) = 9.59, $p < .001$), such that intention was higher when the app was free than when it was free with ads or paid. At low existing volume, however, results indicated a product type × dispersion interaction (F(2, 671) = 3.37, $p < .05$); follow-up comparisons revealed that the effect of product type became insignificant when dispersion was also low.

Intention to reciprocate. An ANOVA including the three treatment variables and their interactions revealed a main effect of product type (F(2, 671) = 17.82, $p < .001$), such that intention to reciprocate was higher in the free condition than the free + ads condition (M = 5.50 vs. M = 4.97; F(1, 671) = 16.71, $p < .001$) or the paid condition (M = 4.73; $F_{(1,\ 671)} = 33.61$, $p < .001$). To investigate the reciprocity pathway formally, we conducted a mediation analysis similar to that of Study 2, including only the free and paid conditions. Consistent with hypotheses, results revealed an indirect, negative effect of product type on intention to post through intention to reciprocate (B = −.87, SE = .21, 95% CI = [−1.28, −.46]).

To address the potential roles of attitude toward the app, self-serving motivation, and chance of survival, we added these variables to the mediation model. Results did not support a mediating role for attitude toward the app or self-serving motivation (95% CIs included zero), but did support a mediating role for chance of survival (B = −.18, SE = .09, 95% CI = [−.41, −.04]), suggesting that participants were more willing to post reviews for free apps owing to the perception that those apps were more likely to survive. However, results continued to support a mediating role for intention to reciprocate (B = −.69, SE = .18, 95% CI = [−1.07, −.36]).

Perceived adoption risk. An ANOVA revealed significant main effects of product type (F(2, 671) = 4.14, $p < .05$), volume (F(1, 671) = 16.51, $p < .001$), and dispersion (F(1, 671) = 19.52, $p < .001$). Most importantly, the ANOVA also revealed a marginal product type × volume × dispersion interaction (F(2, 671) = 2.48, $p = .08$) whose pattern was consistent with predictions. Under a combination of low volume and high dispersion, perceived adoption risk was lower when the app was free than when it was free with ads or paid ($M_{free} = 2.83$ vs. $M_{free\ +\ ads} = 3.37$; F(1, 671) = 10.94, $p < .001$; $M_{paid} = 3.44$; F(1, 671) = 14.20, $p < .001$). For all other combinations of volume and dispersion, perceived adoption risk did not significantly differ by product type ($p > .30$).

To investigate the adoption risk pathway formally, we conducted a moderated mediation analysis similar to that in Study 2. Consistent with hypotheses, results supported an indirect, positive effect of product type on intention to post through perceived adoption risk, which was moderated by the volume × dispersion interaction (B = −.16, SE = .11, 95% CI = [−.48, −.01]). The indirect effect was reliable at a combination of low volume and high dispersion (B = .13, SE = .08, 95% CI = [.01, .32]), but not at any of the other volume × dispersion conditions (all CIs contain zero).

Discussion

Extending the results of Studies 1 and 2, our third study provided convergent evidence for the two pathways in our framework. In support of the reciprocity pathway, sharing intention was stronger when a product was "free" than when the producer was "paid" (either directly or indirectly). Supporting the risk pathway, however, this difference was virtually eliminated when existing product WOM signaled high levels of adoption risk.

[6] When past usage is controlled for, results are similar to those reported in the text (see Web Appendix E).

Results for the new free + ads condition were largely similar to those in the paid condition. Tentatively, the similarity can be interpreted to mean that salient noneconomic costs were perceived similarly to economic costs, such that they reduced motivation to share WOM as a means of reciprocation, but increased motivation to share WOM as a means of helping others limit risk.

Study 4: Field Data—Actual WOM Sharing for Mobile Apps

Research Setting and Methodology

Conclusions from the first three studies are limited by inherent design limitations. For example, Study 1 relied heavily on participants' memory, and Studies 2 and 3 required participants to "experience" a product that they had not actually sought out or chosen; "payment" in paid conditions was either facilitated by study compensation (Study 2) or hypothetical (Study 3). To address these limitations, our final study involved an archival analysis of real-world data from the two leading mobile app platforms: Google's Google Play store and Apple's App Store. In 2016, the two platforms were responsible for 100 billion downloads and more than $35 billion in revenue. Pricing on the platforms varies considerably, with a large proportion of developers utilizing free-pricing models. Moreover, both platforms allow users to easily view prior app reviews or post their own. The accumulation of reviews is critical to developers, as reviews play a direct role in adoption decisions and also affect the visibility of apps on the platforms. In summary, this setting provides an externally valid and meaningful context for testing our framework.

To explore how product type and existing WOM influence subsequent review posting, we restricted our sample to apps available at both platforms and implemented a difference-in-differences estimation approach (Chevalier and Mayzlin 2006; Sun 2012; Zhu and Zhang 2010). By focusing on differences between the two platforms for the same apps, we could largely eliminate unobserved heterogeneity across apps that may affect pricing or sharing. By comparing this difference at two points in time, we could control for platform-specific characteristics.

Model Specification

We define $\text{NewReviews}_{it}^{K}$ as the total number of reviews posted at time t for a specific app i listed on platform K (where K is either Google Play or the App Store). $\text{NewReviews}_{it}^{K}$ is specified as a function of the following variables. First, to represent whether app i is free at time t, we include the dummy variable Free (equal to 1 if free and 0 otherwise). Second, the existing volume and dispersion of reviews for app i at time t are measured by two dummy variables: Low Volume (LV, equal to 1 if app i's review volume is low and 0 otherwise), and High Dispersion (HD, equal to 1 if app i's review dispersion is high and 0 otherwise). We also include the interactions of LV, HD, and Free,[7] resulting in the following specification:

$$\begin{aligned}\text{NewReviews}_{it}^{K} = {} & \beta_1\text{Free}_{it}^{K} + \beta_2\text{LV}_{it}^{K} + \beta_3\text{HD}_{it}^{K} + \beta_4\text{Free}_{it}^{K} \\ & \times \text{LV}_{it}^{K} + \beta_5\text{Free}_{it}^{K} \times \text{HD}_{it}^{K} + \beta_6\text{LV}_{it}^{K} \\ & \times \text{HD}_{it}^{K} + \beta_7\text{Free}_{it}^{K} \times \text{LV}_{it}^{K} \times \text{HD}_{it}^{K} \\ & + \text{Controls}_{it}^{K} + v_i + \mu_i^{K} + \epsilon_{it}.\end{aligned} \tag{1}$$

The variable v_i captures app-level fixed effects, and the variable μ_i^K captures platform-level fixed effects. An important concern is that free pricing might reasonably be expected to generate greater demand, which would, in turn, result in more reviews. Therefore, we include in Controls_{it}^{K} two ranking dummy variables: OverallTop500 indicates whether app i was ranked among the top 500 apps for platform K at time t, and CategoryTop500 indicates whether app i was ranked among the top 500 apps in its category.[8] Another concern is that paid apps might be higher in quality, which may itself affect the accumulation of reviews. Therefore, we include in Controls_{it}^{K} the variable Rating, indicating the average customer rating of app i in platform K at time t.

Our framework predicts that changing from a paid app to a free app will have a positive effect on review posting, but that this effect will be attenuated when existing WOM provides a strong signal of user risk (i.e., when volume is low and dispersion is high). Thus, we are most interested in the coefficients β_1 and β_7. An implicit assumption is that the price and existing WOM of an app at one platform have little influence on review sharing for the same app at the other platform. We believe this assumption to be reasonable (given that the platforms are incompatible), and our approach is consistent with other work (e.g., Zhu and Zhang 2010).

To remove app-specific effects v_i, we take the difference in NewReviews_{it} between Google Play (denoted by the superscript G) and the App Store (denoted A), resulting in the following:

$$\begin{aligned}\Delta\text{NewReviews}_{it} = {} & \beta_1\Delta\text{Free}_{it} + \beta_2\Delta\text{LV}_{it} + \beta_3\Delta\text{HD}_{it} \\ & + \beta_4\Delta\text{Free}_{it} \times \text{LV}_{it} + \beta_5\Delta\text{Free}_{it} \times \text{HD}_{it} \\ & + \beta_6\Delta\text{LV}_{it} \times \text{HD}_{it} + \beta_7\Delta\text{Free}_{it} \times \text{LV}_{it} \\ & \times \text{HD}_{it} + \Delta\text{Controls}_{it} + (\mu_i^{G} - \mu_i^{A}) + \epsilon_{it},\end{aligned} \tag{2}$$

where $\Delta\text{NewReviews}_{it} = \text{NewReviews}_{it}^{G} - \text{NewReviews}_{it}^{A}$, $\Delta\text{Free}_{it} = \text{Free}_{it}^{G} - \text{Free}_{it}^{A}$, $\Delta\text{LV}_{it} = \text{LV}_{it}^{G} - \text{LV}_{it}^{A}$, $\Delta\text{HD}_{it} = \text{HD}_{it}^{G} - \text{HD}_{it}^{A}$, and so on.

[7] Given that our specification includes two- and three-way interaction terms, use of dummy measures for volume and dispersion greatly alleviates interpretation. As a robustness check, we employ continuous measures (see the following discussion).

[8] The primary determinant of an app's ranking is number of downloads. We were unable to utilize exact ranks, as this information was unavailable for apps ranked below 500.

Table 1. Study 4: Summary Statistics.

	September 2014		March 2015	
	Google Play	Apple's App Store	Google Play	Apple's App Store
	(1)	(2)	(3)	(4)
New reviews	863.404 (6,587.073)	202.325 (2,043.706)	753.743 (4,351.575)	132.452 (1,081.750)
Proportion of free apps	.679 (.467)	.635 (.481)	.684 (.465)	.641 (.480)
Prior review volume	8,915.005 (42,197.590)	7,180.056 (42,981.800)	14,638.600 (81,428.460)	8,191.173 (48,467.830)
Prior review dispersion	1.300 (.426)	1.254 (.426)	1.329 (.388)	1.283 (.402)
Prior rating	3.747 (.817)	3.693 (.919)	3.732 (.792)	3.671 (.905)
Overall rank top 500	.066 (.248)	.045 (.207)	.057 (.231)	.041 (.198)
Category rank top 500	.670 (.470)	.543 (.498)	.637 (.481)	.539 (.499)
Number of observations	5,665	5,665	5,665	5,665

To remove the platform-specific effect ($\mu^G{}_i - \mu^A{}_i$), we next take the difference in Equation 2 between time t and time t + 1. The result is the main specification for our analyses:

$$\begin{aligned}\Delta\Delta\text{NewReviews}_{it} = {} & \beta_1\Delta\Delta\text{Free}_{it} + \beta_2\Delta\Delta\text{LV}_{it} + \beta_3\Delta\Delta\text{HD}_{it} \\ & + \beta_4\Delta\Delta\text{Free}_{it} \times \text{LV}_{it} + \beta_5\Delta\Delta\text{Free}_{it} \\ & \times \text{HD}_{it} + \beta_6\Delta\Delta\text{LV}_{it} \times \text{HD}_{it} + \beta_7\Delta\Delta\text{Free}_{it} \\ & \times \text{LV}_{it} \times \text{HD}_{it} + \Delta\Delta\text{Controls}_{it} + \epsilon_{it}.\end{aligned} \tag{3}$$

Data and Summary Statistics

We randomly selected 6,300 apps available at both Google Play and the App Store between September 2014 and March 2015. Of these 6,300 apps, 5,954 had received at least one review by September 1, 2014. We removed 289 "corporate" apps intended to support offline businesses (banking, airline, hotel, etc.), because motivations in that category are likely to be unique. Our final sample consisted of 5,665 apps and included prices, review distributions, and rankings at both platforms for the September 2014 and March 2015 periods.

Table 1 presents the means and standard deviations of key variables. The majority of apps on both platforms were free (68% on Google Play vs. 64% on the App Store). Apps on Google Play received substantially more reviews than those on the App Store during the sample periods, which likely reflects the larger Android user base. Apps on Google Play were rated slightly higher than those at the App Store, and their ratings were somewhat more disperse.

As model-free evidence, Figure 5 presents the number of new reviews for free and paid apps and for different distributions of existing WOM. Providing initial support for our claims, free apps received more new reviews than paid apps when the existing volume was high (regardless of dispersion), or when existing reviews were homogeneous (regardless of volume), but the difference was negligible for apps with a limited number of disperse reviews.

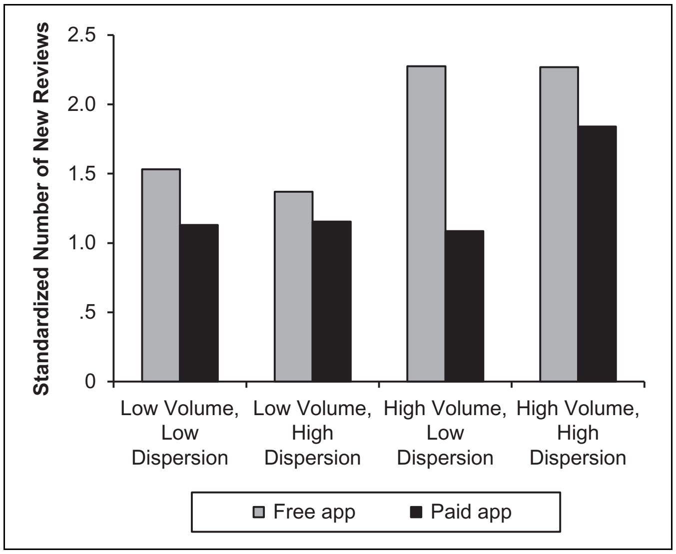

Figure 5. Study 4: Descriptive evidence.

Notes: The chart is based on the September 2014 sample; "high and "low" levels are defined by a median split; the difference in new reviews between free and paid apps is significant for all groups (ps $< .06$) except the "low volume, high dispersion" group.

Results

Table 2 presents baseline regression results for specification 3. Because the number of new reviews (NewReviews_{it}) was highly skewed, we applied a log-transformation to this variable. The low-volume and high-dispersion categories were assigned by median split.

Column 1 in Table 2 contains no interaction terms or control variables, and column 2 adds control variables. Unsurprisingly, both OverallTop500 and CategoryTop500 were positively correlated with number of new reviews (i.e., more popular apps attract more reviews). More importantly, the coefficient of $\Delta\Delta$Free is significant and positive for both models. The magnitude of the effect can be illustrated as follows: were a paid app that normally receives 100 monthly reviews to become free, it would be expected to receive 222 monthly reviews.

Column 3 adds interaction terms to the specification in column 1, and column 4 adds back control variables. Examination of column 4 reveals evidence for both key predictions. The coefficient of $\Delta\Delta$Free remains significant and positive, suggesting that the likelihood of posting WOM for free products

Table 2. Study 4: Baseline Results.

Dependent variable: ΔΔlog(NewReviews)	(1)	(2)	(3)	(4)
ΔΔFree	1.199*** (.176)	1.229*** (.170)	1.269*** (.193)	1.294*** (.189)
ΔΔLV		−.094 (.061)	−.082 (.145)	−.087 (.144)
ΔΔHD		−.069 (.047)	−.162 (.162)	−.209 (.163)
ΔΔFree × LV			−.023 (.165)	−.012 (.164)
ΔΔFree × HD			.062 (.175)	.113 (.176)
ΔΔLV × HD			.340** (.168)	.382** (.170)
ΔΔFree × LV × HD			−.403** (.187)	−.447** (.188)
ΔΔRating		−.006 (.065)		−.001 (.065)
ΔΔOverallTop500		.371*** (.078)		.377*** (.078)
ΔΔCategoryTop500		.140*** (.026)		.139*** (.026)
Observations	5,665	5,665	5,665	5,665
R-squared	.016	.023	.020	.032

$^{**}p < .05$.
$^{***}p < .01$.
Notes: Robust standard errors in parentheses; ΔΔ indicates differences between the two platforms and between the two points in time.

Table 3. Study 4: Marginal Effects.

Effects of Changing from Paid to Free on New Posts			
Low Volume		High Volume	
Low Dispersion	High Dispersion	Low Dispersion	High Dispersion
1.282*** (.187)	.948*** (.199)	1.294*** (.189)	1.407*** (.213)

$^{***}p < .01$.
Notes: Marginal effects are calculated using the estimates in column 4 of Table 2; robust standard errors in parentheses; the difference between the low volume, high dispersion condition and the other three conditions is statistically significant (ps $< .05$).

is generally greater than that for paid products. The coefficient of ΔΔFree × LV × HD is significant and negative, suggesting that the positive effects of free pricing on posting are attenuated when existing WOM implies high adoption risk.[9]

Table 3 presents marginal effects of changing from "paid" to "free" on new monthly posts. The marginal effect is smallest in the low-volume, high-dispersion group ($LV = 1$, $HD = 1$), and the marginal effect in this group is significantly smaller than that in the other three groups. To illustrate, assume that a paid app that normally receives 100 monthly reviews becomes free. If the app has a large volume of existing reviews or those reviews are highly disperse, then our estimates predict 228–240 new monthly reviews. If the app has accumulated a low volume of heterogeneous reviews, then our estimates predict only 194 new monthly reviews.

Through a series of robustness checks, presented in Web Appendix F, we (1) employed continuous measures for existing volume and dispersion, (2) restricted the sample to apps with high average rating (at least four out of five), and (3) implemented a cross-sectional analysis. Results of all checks were qualitatively similar to the baseline results.

Discussion

The main findings of Study 4 were consistent with our framework and results of the first three studies. Free pricing appeared to stimulate WOM sharing (in the form of reviews), but this stimulating effect was reduced when existing WOM signaled high adoption risk. Though the "real-world" empirical setting precluded direct measure of underlying psychological processes, it enabled an externally valid demonstration of free pricing effects on actual customer WOM.

General Discussion

Despite the recent proliferation of "freemium" and related business models, extant research offers surprisingly few insights regarding the implications of free-product settings for WOM. Addressing this gap, our theoretical framework highlights two characteristics that distinguish free products from their paid counterparts—reciprocity and lower adoption risk—and argues that these characteristics bear distinct implications for sharing. On the one hand, reciprocity facilitates motivational effects oriented toward producers, as consumers of free products seek to "give back in return" for benefits provided at no (monetary) cost. In our studies, this pathway was supported by a *positive*, large, and consistent effect of free pricing on willingness to provide WOM, mediated by intentions to reciprocate. On the other hand, adoption risk facilitates motivational effects oriented toward other potential adopters, as consumers of paid products seek to help others with their decisions. In our studies, this pathway was supported by a *negative*, moderate, and

[9] The sample pool undoubtedly contained artificial or "robot" reviews. However, we do not deem them a threat to our interpretation, as they cannot easily explain the observed effects of Free or its interactions. The removal of app-specific effects allays any concern that robot reviews were distributed unevenly across apps.

consistent effect of free pricing on willingness to provide WOM, mediated by perceptions of adoption risk. Consistent with the notion of distinct pathways, the second pathway (but not the first) was sensitive to aspects of existing WOM that signal adoption risk.

Although WOM is typically portrayed as a self-serving behavior, scholars are increasingly aware that this portrayal is incomplete and have emphasized the need to examine more altruistic motivations (Berger 2014). To this end, our findings suggest that product-related WOM is influenced by the motivation to help both producers and other consumers. However, we acknowledge that these motivations might also be self-serving: for example, "reciprocating" to app developers through positive WOM might also help customers avoid feeling guilty, and "providing useful information" to potential adopters might also enhance status or reputation. Nonetheless, our focus on other-oriented motivations provides a useful supplement to other approaches.

For both pragmatic reasons (keeping the theory tractable) and practical reasons (producers stand the most to gain from positive WOM), our theorizing required the assumption of a satisfactory consumption experience. Were this assumption to be dropped, it is reasonable to expect that dissatisfaction would interfere with the reciprocity pathway (i.e., the desire to "give back" in exchange for free pricing would logically diminish when a product does not perform as expected). Implications of dissatisfaction for the adoption risk pathway are less clear, and we encourage additional exploration. Similarly, our theorizing assumes minimal discrepancy between the consensus of prior WOM and the experience of the current user. The implications of discrepancy are nonobvious and worthy of investigation.

Participants in our two experiments engaged in "one-shot transactions" with the seller, limiting opportunities for learning or relationship formation. Repeated interactions would presumably alter the nature of the relationship in ways that would impact our findings: in particular, repeated interactions might influence both the magnitude of reciprocity motivation and its ramifications for WOM. Research addressing this issue would be fruitful.

Intuitively, a sufficiently large volume of existing WOM could discourage consumers from providing their own, even in free-product settings. This intuition is consistent with the "crowding-out" effect observed in charitable donation contexts (Abrams and Schitz 1978). However, our data do not show evidence of such an effect, and our theory does not predict it. In contrast to charitable contexts, in which the goal is to help a target in need or contribute to the greater good, our reciprocity mechanism involves the goal of paying back a personal debt to the provider of a free product. To the extent that a "personal" debt cannot be paid by others, reciprocity cannot be "crowded out," and consumers of free products should feel compelled to share WOM even when voluminous prior WOM is available.

In practice, free-product pricing underlies a wide variety of pricing and revenue models (penetration pricing, freemium and tiered models, complementary pricing, etc.). Considering the implications of each is outside the scope of our research, but our findings offer initial insights. On the one hand, results were positive and consistent for the free conditions of Study 2 (in which no explanation was provided), Study 3 (in which participants were explicitly informed of a freemium pricing model), and Study 4 (which involved a diverse range of free apps). On the other hand, the positive impact of free pricing on reciprocity diminished in the free + ads condition of Study 3, in which the presence of a nonmonetary cost was salient. Thus, participant inferences regarding the "true cost" of free pricing seemed to play an important role in psychological and behavioral responses. We encourage further exploration of those inferences.

Our results suggest that zero-cost pricing is generally facilitative to WOM. Although it is unrealistic to base pricing decisions on this benefit alone, it is clearly relevant to firms that are actively considering a free-pricing strategy and to market contexts in which rapid awareness or network effects are important; in online retail, for example, the accumulation of online WOM increases adoption rates by as much as 270% (Askalidis and Malthouse 2016). Based on a simple profit-maximization model and the effect sizes observed in Study 4, the free-to-paid conversion rate required for a freemium strategy to outperform a paid strategy is halved when the beneficial effects of free pricing on WOM are incorporated.[10]

The very concept of "free" is debatable in both legal and economic senses (Evans 2011; Newman 2015). We acknowledge that given reasonable assumptions, a truly "free" product may not exist—or may not be sustainable in the marketplace. Nonetheless, free-product pricing is commonplace in many categories, and a long line of consumer research indicates that framing a product as "free" induces consumers to think, feel, and behave differently (Shampanier, Mazar, and Ariely 2007). In such research, "free" is typically defined in terms of monetary cost, and buyers are shown to be remarkably insensitive to nonmonetary costs. Adopting a similar perspective, we suggest that our framework applies broadly to products that are perceived as free, regardless of whether the perception is rational.

By revealing important differences in consumer motivation between free- and paid-product settings, our findings suggest distinct strategies for generating WOM. Within free-product settings, in which reciprocity toward the producer is an important catalyst of WOM, marketers may find it worthwhile to embed reciprocity cues overtly in their communications. For example, postconsumption messaging often encourages customers to "spread the word" or "tell your friends about us"; within such messaging, marketers might explicitly remind customers of their satisfactory experience and the firm's role in bringing that experience about. In paid-product settings, marketers may find it more worthwhile to highlight the diverse value of WOM to other shoppers (e.g., "save them time," "help them decide"). When applicable, WOM solicitations might emphasize that the quantity of existing reviews is lacking or previous customers have diverged in their opinions (or both).

[10] Details are available from the authors upon request.

As a result of these different communicational emphases, potential contributors will be directed to contextual cues that motivate sharing.

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