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The sales effect of “Free App of the Day” on Amazon Appstore: An empirical study



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ABSTRACT

This study aims to understand the impact of the “Free App of the Day” (FAD) promotion on app sales during the post-promotion period on Amazon Appstore. The FAD promotion spotlights a single paid app by presenting it on the frontpage of Appstore, offers the app free of charge for one day, and broadcasts the promotion through Amazon's social media channels. This digital marketing strategy differs from the commonly adopted digital free sampling and sponsorship practices. In this study, we empirically examine its potential negative effect by analyzing a panel data set of FAD app sales and reviews. We find evidence that, when the app promotion expires, the price rebounding to the pre-promotion level discourages online customers from purchasing the app. We also observe an elevated amount of promotion-induced reviews generated at a high velocity during early days of the post-promotion. We conclude that these promotion-induced reviews are less influential than organic reviews.

1. Introduction

Apps, as an abbreviation of mobile applications, are software products for mobile platforms (Tang, 2016). They are designed to perform certain tasks on mobile devices (Islam, Islam, & Mazumder, 2010). This product category has grown to become a gigantic differentiated market with over 3.48 million apps on Google Play, an app marketplace, and the recent projection of over 935-billion-dollar revenue in 2023 (Statista Research, 2021a, 2021b). As a result, there is a strong need for app developers and app platforms to design innovative and effective marketing strategies to enhance visibility of their products and proactively attract new customers. A successful example is the electronic Word-of-Mouth (eWOM) marketing strategy, which encourages and solicits online user reviews and feedback to raise consumer awareness of the product, disseminate product information, and promote sales. eWOM strategy is found most effective on the experiential products, e.g., apps, whose product attributes are abstract and difficult to evaluate before consumption (Sharma & Pandey, 2011). To help app developers promote their apps and compete for a unique position from other dominating Android app marketplaces (e.g., Google Play), from

March to August in 2015, Amazon Appstore introduced a unique promotion, “Free App of the Day” (FAD).

FAD spotlighted one single paid app on its front page every day and, at the same time, temporarily priced it as a free app for 24 hours. In essence, Amazon Appstore attempted to utilize the features from two commonly adopted practices in the digital product market: 1) digital free sampling that offers a free copy of the digital product either with limited functionalities or for a limited time, and 2) sponsorship practices that feature the advertised digital product at the top noticeable position of the e-commerce platform. In particular, it shared the key feature, zero-price offering, with digital free sampling, which has been shown to reach new customers and reduce transaction costs (Bawa & Shoemaker, 2004; Cheng & Liu, 2012; Han & Zhang, 2018; Peitz & Waelbroeck, 2006). In addition, like sponsorship practices, it spotlighted the app to increase the visibility and enhance customer awareness of the app.

This type of FAD promotion is not uncommon at the digital platforms. Apple App Store launched a similar Free App of the Day program in 2012 (Peterson, 2017). In 2017, Google also created a similar promotion in its Google Play app store as “Free App of the Week” by offering a paid app free of charge for a week (Protalinski, 2017). On August 2015, Amazon

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even expanded the FAD into a more comprehensive Amazon Underground platform to include more apps without the time limitation on the free offering (Singleton, 2015). However, Google Pay's "Free App of the Week" lasted for three weeks (Cervantes, 2017). Apple's FAD discontinued in 2017 (Peterson, 2017). Amazon closed the Underground in 2019 and decided to focus on the regular Amazon Appstore (Liptak, 2017; Perez, 2017). We wonder the potential causes to the discontinuation of this type of FAD promotion at major app stores.

It is tempting to simply assume that FAD promotion is effective, as it combines features from two popular marketing strategies, digital free sampling, and the sponsorship. FAD apps experience a transition from an onstage (in-promotion) to an offstage period (post-promotion). The app's in-promotion sales are expected to increase in the same way as free sampling and sponsorship practices would benefit sales. However, can FAD be a double-edged sword? In this work, we are interested in whether the promoted app loses momentum during the post-promotion period. To our best knowledge, there is no prior study that specifically measures and interprets the impact of FAD promotions. The answer to this question can help firms and online platforms make an evidence-based decision on the adoption of this type of promotion practice. For practitioners, it can also raise the importance of evaluating a marketing strategy throughout its entire lifespan, including the in-promotion and post-promotion periods.

In addition, such exploration can help interpret the impacts of two important features of FAD promotion, temporary zero-price offering and spotlighting, on post-promotion sales. It is inappropriate to directly apply the findings from free sampling and sponsorship into understanding the FAD promotion.

First, the practice of digital free sampling normally offers a free version of the app concurrently along with its paid version, yet with either fewer functionalities or limited time usage (Lee & Tan, 2013). However, FAD apps are totally the same as their paid version in both functionalities and time usage, and they are not offered at the same time with the paid version. In addition, the price of FAD apps returns to the regular price as soon as the promotion ends. Therefore, prior findings from digital free sampling cannot fully explain the effects of zero-price offering from the FAD promotion.

Second, eWOM, e.g., online user reviews, generated through the FAD promotion is likely in a much larger volume than those generated through the sponsorship. Sponsorship practice stages the products in the spotlight to reach to a broad user base, and in turn, generated eWOM from those new users. This is applicable to FAD promotion as well. However, FAD can attract user conversations in an additional avenue. During the FAD in-promotion period, the removal of the purchase cost to experience the promoted app expands the user base, and the high visibility of the app motivates more users to share their experiences (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). As a result, prior findings on the sponsorship's eWOM effect can be different from the FAD promotion.

To study the potential unexpected effect of FAD, in this work, we hypothesize two factors that may negatively influence the sales of the FAD app: price rebound and promotion-induced user reviews. First, during the post-promotion period, new buyers may be sensitive to the price rebound, which refers to when the price rises from zero to its pre-promotion price. They thereby develop adverse reactions that discourage sales (Lin, Hsu, & Chen, 2013; Niemand, Mai, & Kraus, 2019). This has not been investigated yet in the literature of digital free sampling, mainly because most free sampling strategies offer both free and paid versions simultaneously and do not encounter price rebound. Second, user reviews explosively gained during the first few days of post-promotion may be less influential on app sales than organic reviews generated gradually and consistently. We define the reviews generated as a result of FAD promotion as *promotion-induced reviews*, which are different from *organic reviews* that occur gradually and naturally (Ballantine Paul & Au Yeung, 2015; Kim, Maslowska, & Tamaddoni, 2019). Extant studies on comparing organic and non-organic reviews generally concern a limited number of incentivized reviews (Ballantine Paul & Au Yeung, 2015; Kim et al., 2019; Kim & Song, 2018), as the incentive system is selectively open to a small group of users with an unclear selection process. However, FAD promotion is different in that it attracts all users in a

broader group. Therefore, this calls for a need to carefully compare the impact of promotion-induced and organic reviews on FAD apps.

We collected a daily panel data set of 34 FAD apps over 43 days during 2015 by using a web crawler. We tracked each app for 10 days, starting from the first day when the apps were promoted in FAD, and the subsequent nine days during the post-promotion period. By conducting exploratory analysis and regression modeling, we find evidence that supports our hypotheses. We observe that the benefit of FAD promotion quickly exhausts: on average, sales drops from the third day of post-promotion. The price rebound and the flooded promotion-induced reviews are used to explain such decrease. A sharper price rebound is associated with lower app sales; conditional on the total volume of user reviews, app sales benefit less from promotion-induced reviews than organic reviews. These results offer some partial explanations to the discontinuation of FAD program and its similar forms at Amazon, Apple, and Google app stores in recent years.

In the following two sections, we present a review of literature and propose our hypotheses, respectively. This is followed by Data in Section 4, Empirical Analysis in Section 5, and a discussion of conclusions, limitations, and directions for future research in Section 6.

2. Literature review

In this section, we briefly review the most relevant literature on digital free sampling and eWOM effects in the online market and discuss the main differentiations of our work from them.

2.1. Digital free sampling

Free sampling has been commonly seen in traditional physical goods, such as free samples of toothpaste, skincare, and food in a much smaller volume than the commercial products. In recent years, a particular practice of free sampling, free digital sampling as a natural extension of physical free samples in brick-and-mortar business, has gained popularity in e-commerce by offering the digital copy free of charge in the markets of digital products, such as app, software, book, music, among others. These free digital samples generally come in either of the two following different approaches: offering the product with limited functionalities for lifetime; offering the full-version product for a limited time (Chen, Duan, & Zhou, 2017; Wang & Zhang, 2009). Strictly speaking, FAD doesn't fall into either category, because FAD apps have the full functionalities without time limit. Therefore, studying the FAD promotion adds to the empirical evidence for the possibility of a new way to offer free samples.

Most of the analytical and empirical literature on digital free sampling examines the impact of digital free sampling on market outcomes (Cheng & Liu, 2012; Lee & Tan, 2013; Lin, Zhang, & Tan, 2019; Shi, Xia, & Huang, 2015; Che et al., 2017). The results are twofold. Offering digital free samples introduces the product to customers who would otherwise never try the product at very low costs. At the same time, digital free samples serve as substitutes to some customers and thus cannibalize demands for the paid full version.

As a distinction from those studies, we focus on the effect of the removal of the free offering on the market outcomes during the post-promotion. The 24-hour only offering of FAD promotion allows us to study it, which is not feasible in the contexts of previous works on free sampling. Digital free samples are made available by developers and are in large offerings for a long time period (Chen et al., 2017), while FAD promotion is initiated by the platform (Amazon.com) that offers one single app at a time for 24 hours. In addition, a digital free sample generally has differences with its paid version in functionality or usage (Cheng & Liu, 2012). FAD app is essentially the same as the paid version with the exact same functionality and usage. As a result, studying the aftermath of FAD can offer unique understandings on adopting temporary zero price in e-commerce of digital products such as apps.

2.2. eWOM

This work also relates to studies on the economic value of eWOM in an online context (Genc-Nayebi & Abran, 2017). As one of the most popular forms of eWOM, online user reviews are generated by users after consumption. As a result, they are believed to be different from commercial advertisements (Tellis, MacInnis, Tirunillai, & Zhang, 2019). Attribution theory has been used to explain how online users process eWOM information (Qiu & Li, 2010). Attribution theory explains a process in which individuals make a causal inference from others' choices and behaviors. This theory highlights a discounting principle that in presence of other plausible causes, people discount the value of a given cause (Kelley, 1972). For example, online customers tend to discount an individual customer's positive review (a given cause), when the aggregate rating is negative (other plausible causes) (Qiu & Li, 2010).

eWOM is found to be influential on sales, even more than advertisements created by brands (Chevalier & Mayzlin, 2006; Sharma & Pandey, 2011). Prior studies have identified some eWOM measures that have different information values and thus affect online user decisions differently. For example, volume captures the total number of online user conversations. It is argued to indicate online customer awareness of the product: more user discussions can increase the visibility of the product and introduce the product to more customers (Babić Rosario, Sotgiu, De Valck, & Bijmolt, 2016; Liu, 2006; Risselada, De Vries, & Verstappen, 2018; Zhou & Duan, 2015). Valence, generally measured by the average user rating, implies the level of product quality perceived by customers (Duan, Gu, & Whinston, 2008; Gavilan, Avello, & Martinez-Navarro, 2018; Lu, Ba, Huang, & Feng, 2013). More recent works have also differentiated between organic reviews and non-organic reviews in online communities (Kim et al., 2019; Kim & Song, 2018; Litvin & Sobel, 2018). The consensus from this comparison is that organic reviews are less positive and more objective and perceived more credible and helpful (Kim et al., 2019; Litvin & Sobel, 2018).

Spotlighting and temporarily offering a paid app free of charge can solicit a surge in promotion-induced user conversations (Ballantine Paul & Au Yeung, 2015; Kim et al., 2019). Although there have been already a handful recent studies on comparing organic reviews and non-organic reviews in online communities (Kim & Song, 2018), our study on FAD contributes to this line of research by the following two aspects. First, prior works focus on incentivized reviews created by a small number of customers who are selected in private processes to receive some form of monetary compensation (Gerrath & Usrey, 2020; Kim et al., 2019; Kim & Song, 2018). In contrast, FAD is a process that casts the spotlight on a single app to solicit reviews from all users on the platform. In other words, FAD's incentivization is open and transparent. Second, one of the challenges is to differentiate non-organic reviews from organic ones. It is because not all incentivized reviewers disclose the company sponsorship along with their written reviews. Our work tries to propose two simple measures that could be helpful for this differentiation.

3. Hypotheses

In this section, we discuss our hypotheses on the price rebound caused by the removal of zero-price offering and the eWOM generated through the FAD during the post-promotion period.

Prior studies on free pricing suggest that customers with a free mentality, a belief which expects all digital offerings to be free, have a less positive attitude towards paid products (Lin et al., 2013). We propose that such free mentality plays a role in FAD promotion. Offering an app for free activates the free mentality of customers towards that product, and therefore, discourages future adoptions after the offer expires (Niemand et al., 2019).

This negative impact of price rebound on the post-promotion product adoptions is also supported by the psychological inference on zero price that links free products with low quality (Niemand et al., 2019). Customers may perceive these FAD apps that have been offered free as of low quality, especially when apps, as a typical type of experience goods, exert difficulties for users to evaluate their quality before consumption.

We further argue that a sharper post-promotion price rebound leads to a greater negative impact on app sales. The price drop and the subsequent rollback are the salient behaviors of apps retreating from FAD. These behaviors directly connect to extant empirical studies around price adjustment of consumer products and its related adverse effects, particularly the customer antagonism (Anderson & Simester, 2010) and the drop of consumer reference price (Mazumdar, Raj, & Sinha, 2005). Customers are antagonized as the reaction to upward price adjustment, which could induce a negative shift in their expectation about future price (Okun, 1981; Phelps & Winter, 1970). To prevent customer antagonization, firms are generally believed in and applying the practice of sticky price, i.e., keeping product price with very limited variation (Renner & Tyran, 2004). If firms must raise the price, price obfuscation, a practice in which firms intentionally make the price comparison complex, is normally recommended so that it is difficult for customers to observe the price history (Ellison, 2006; Ellison & Ellison, 2009). Nevertheless, the current and past FAD promotions can be conveniently discovered through other prevalent social media platforms, e.g., Facebook and twitter. As a result, price obfuscation is unlikely to succeed in this context, leading to user awareness of the historical zero-price offering. Further, the likelihood of antagonizing customers is higher when price rebound is sharper, which leads to a greater chance to discourage purchases.

The internal reference price, which refers to an internal price standard for customers to compare against an observed price, also supports this argument. Empirical evidence shows that the formation of the price standard partially relies on the past prices (Mazumdar et al., 2005). In our work, a consumer can use the past zero price as an internal reference price to decide whether to purchase that app at full price. The customers perceive net loss when a current observed price is higher than the reference price. The larger difference between rebounded price and the zero reference price will discourage user adoptions of the products and purchases (Thaler, 1985).

Therefore, we propose the following hypothesis:

H1. Online user decisions of adopting apps are discouraged by the price rebound after the zero-price offering of FAD ends. The sharper price rebound leads to a greater decrease in app adoptions.

There is no doubt that FAD helps bring in a lot of user conversations. There are two main reasons for the surge of promotion-induced reviews after FAD ends: 1) an expanded user base due to the promotion, and 2) a higher percentage of users who are willing to review the previously spotlighted apps. The user base gets expanded through attracting new customers by FAD's high visibility and zero price. A larger user base leads to more online user-generated discussions (Liu, 2006; Zhou & Duan, 2015). In addition, prior studies on users' motivations to share online reviews imply that users are more likely to give reviews on high-profile products for a chance of gaining self-enhancement and recognition from online community (Goes, Lin, & Au Yeung, 2014; Hennig-Thurau et al., 2004). Self-enhancement is defined as users' emotional desires to gain attention and enhance their images among others (Dichter, 1966; Sundaram, Mitra, & Webster, 1998). Hennig-Thurau et al. (2004) have empirically verified that self-enhancement has a significant impact on the number of comments in online opinion platforms. Therefore, we expect a rapid increase in the volume of promotion-induced reviews as a result of a larger promotion-induced user base and a higher likelihood to share, right after the promotion ends.

We use the time of review publication to differentiate a promotion-induced review from an organic one. We reasonably assume that promotion-induced reviews arrive shortly after the FAD ends and diminish over time. As time passes by since the FAD ends, app reviews will be more likely organic. We intend to quantify this comparison by two relative measures: the relative volume of those two types of reviews, and their relative velocity of entering the platform. The detailed implementation of those two measures can be found in Section 4.

We apply attribution theory in the FAD context to propose that organic reviews affect online user decisions of adopting apps more significantly

than promotion-induced reviews do, conditional on the total volume of user reviews. As reviewed in Section 2, attribution theory suggests that online users discount the value a given cause when there are other plausible causes in presence (Kelley, 1972). Applied in our FAD promotion context, users are likely aware that some reviews are associated with FAD promotion (a given cause). They would thus discount the value of those reviews and rely less on them in making their own decisions, in presence of organic reviews (other plausible causes). Organic reviews could serve as a more informative source, because they are from online users who genuinely decided to try the product and believed the product matched their preferences.

This reasoning is also echoed by the zero-price effect of free sampling. Studies have shown that zero price of free samples triggers affect that people tend to overestimate its benefits and underestimate its costs (Shampanier, Mazar, & Ariely, 2007). In addition, zero price attracts these who are sensitive to the price and only willing to “buy” the app when offered free. As a result, these customer reviews can be of less value to others who needs more unbiased evaluations of apps and are willing to pay the full price.

Following the above studies, we expect that the promotion-induced reviews received after the FAD promotion ends are less influential than organic reviews.

We propose that:

H2. Conditional on the total volume of eWOM, organic reviews are more influential to online user decisions of adopting apps than promotion-induced reviews, after the FAD promotion ends.

4. Data

4.1. Context and data collection

Amazon launched its Appstore for the Android operating system in March 2011. It opened with a small collection of Android apps of around 3800. As of 2015, Amazon Appstore for Android has grown to approximately 300,000 apps. Many developers have decided to sell their apps at Amazon Appstore in addition to Google Play, in hopes of greater exposure to their customer and higher sales. Amazon launched the aforementioned FAD promotion to highlight one single paid app in a day and make it free-of-charge during these 24 hours. During that day, Amazon uses Facebook and Twitter to broadcast the free paid app. In addition to the 24-hour visibility, all FAD apps are archived in the list of “Most Recent Free Apps of the Day” at Amazon Appstore. In addition, Amazon is known for its sophisticated customer review community. Customers can give app reviews by an overall rating in a 5-star rating system along with detailed comments. Amazon summarizes the reviews for each app by an average rating and the total number of reviews, and readily lists this information near the app title. This review community is informative and useful for customers to make purchase/download decisions, especially given the experience goods nature of apps and the extremely overwhelming volume of app offerings.

Our research questions are about the impact of price rebound and eWOM after FAD promotion ends. Therefore, we collected the data of each promoted app starting from the FAD promotion date, named as Day 1, and continued the daily data collection for the subsequent nine days, until Day 10. We implemented such data collection during the period of 06/04/2015–07/23/2015, which provides a balanced panel data set of 34 apps that have practiced FAD promotion. Please note that it is not feasible to acquire a more recent data set of FAD promotion than present 2015 data set. On August 26, 2015, Amazon expanded the FAD into Amazon Underground, which, as an individual platform, hosted hundreds of paid apps free of charge (Singleton, 2015). Therefore, Amazon Underground does not have the same feature of highlighting one single app for a limited time as the FAD promotion.

Specifically, to automate the daily data collection, we developed a Java-based web crawler that parses the app page from Amazon Appstore and extracts the data relevant to our research questions. The web crawler adopts

the snowball process: it runs daily to track the apps that have ended their FAD promotion yet still within 10 days, and add the new FAD promoted App. For each app being collected in that day, we crawled its sales rank, listed price, total number of reviews, average rating, the number of reviews for each rating level (i.e. 5-star, 4-star, etc.), app size, developer, released date, Amazon sequence identification number, version, URL, and other app characteristics. We summarize main variables used in this study in the following Table 1. Some variables are constructed upon the collected data measures, e.g. $SkewDaily_i$ and $KurtDdaily_i$, which will be explained further in the next sub-section 3.2.

Tables 2 and 3 summarize the descriptive statistics of all collected apps and present their correlation matrix, respectively. We find a large variance in most measures, which indicates a good coverage of apps at different stages of product life cycle and with different market shares. For example, our apps include superstar products that had won the best sales rank as well as underdog products that are extremely unpopular with a sale rank below 10,000.

4.2. Key variables

The outcome variable should capture online user decisions of adopting apps at Amazon Appstore. As an alternative to the inaccessible true transaction data, we use Amazon sales rank as the proxy for Amazon sales as our outcome variable. The Pareto relationship between Amazon sales and sales rank has been well established and widely applied in prior studies (Brynjolfsson, Hu, & Smith, 2003; Chevalier & Mayzlin, 2006; Gu, Park, & Konana, 2012). Similarly, we use Amazon sales rank ($SalesRank_{i,t}$) with a negative log transformation ($-Ln(SalesRank_{i,t})$) to approximately measure the log value of actual sales (Ghose & Sundararajan, 2005). It is notable that the collected rank data on the FAD promotion date (Day 1) is in the category of Free Apps, whereas the collected rank data in the rest dates come from the category of Paid Apps. It is not reasonable to compare ranks in two different ranking systems. Therefore, we only keep the data for each app since Day 2 through Day 10 in our analysis related to sales.

We have three key independent variables. The first one measures the magnitude of price rebound, $PriceRebound_{i,t}$, measured as $(AppPrice_{i,t} - AppPrice_{i,1})$, where $t > 1$. It is the difference of post-promotion app price ($AppPrice_{i,t}$) at Day t ($t > 1$) and the app price on the promotion date ($AppPrice_{i,1}$) ($t = 1$). A larger value of $PriceRebound_{i,t}$ indicates a sharper price rebound. In the FAD promotion, $AppPrice_{i,1}$ is equal to 0, but we opt to keep it in the full presentation of this term to be more meaningful.

The other two measures are designed to address one of the challenges in this line of research that user reviews in many contexts do not always explicitly tag promotion-induced reviews. We recognize this limitation exists in our data as well. We propose two metrics as approximate proxies to compare incoming promotion-induced reviews and organic reviews after the promotion ends, by volume of the reviews and the velocity of their creation. As argued in section 2, promotion-induced reviews are mostly generated right after the promotion ends, while organic reviews are naturally created and thus added into the review pool gradually. In other words, promotion-induced reviews outweigh organic reviews shortly after the promotion

Table 1
Variable descriptions.

Variables	Descriptions
i	app i ($i = 1, \dots, 34$)
t	Day t ($t = 1, \dots, 10$)
$SalesRank_{i,t}$	Sales rank of app i at day t
$NumReviews_{i,t}$	Total number of reviews app i receives at day t
$AverageRating_{i,t}$	Average ratings of app i at day t
$VarianceRating_{i,t}$	Rating variance of reviews of app i at day t
$Age_{i,t}$	Days since Amazon has released app i by day t
$AppPrice_{i,t}$	Price offered by Amazon for app i at day t
$Day_{i,t}$	Days since app i was Free App of the Day
$SkewDaily_i$	Skewness of daily number of reviews of app i over nine days
$KurtDdaily_i$	Kurtosis of daily number of reviews of app i over nine days
$AppSize_{i,t}$	The size of the downloadable app i at day t

Table 2
Descriptive statistics.

	Min	Max	Mean	STD
<i>SalesRank_{i,t}</i>	1	10,273	1,156	1,556
<i>NumReviews_{i,t}</i>	4	3950	518	910
<i>AppPrice_{i,t}</i>	0.00	7.99	2.10	1.54
<i>AverageRating_{i,t}</i>	2.60	4.70	3.95	0.46
<i>VarianceRating_{i,t}</i>	0.47	3.32	1.62	0.59
<i>Age_{i,t}</i>	81	1,579	714	445
<i>AppSize_{i,t} (MB)</i>	0.15	240.10	43.37	53.17

ends, however, as time passes by, promotion-induced reviews should fade away and the left are mainly organic reviews. Therefore, the time trend of the incoming reviews over post-promotion days can help capture the comparison between promotion-induced reviews and organic reviews.

Specifically, we resort to two commonly used symmetry statistics: skewness and kurtosis over the daily number of new reviews of Day 2 ~ Day 10, to capture the relative volume (*SkewDaily_i*) and the relative generating velocity (*KurtDdaily_i*) of those two different types of reviews, respectively. We expect a positive *SkewDaily_i* in our review data. This right skewed distribution of daily number of reviews implies the surge of promotion-induced reviews during early days of post-promotion as we argued beforehand, which is supported by the summary statistics reported in the following Table 4. A more positive skewness, indicated by a larger value of *SkewDaily_i*, captures a relatively higher volume of promotion-induced reviews generated right after the promotion ends over organic reviews. Moreover, statistics kurtosis indicates a steeper peak in the skewed distribution of daily number of reviews. In other words, *KurtDdaily_i* captures how quickly such a large volume of promotion-induced reviews are generated. A more positive value of *KurtDdaily_i* implies a relatively higher velocity of generating promotion-induced reviews over organic reviews. In short, more positive values of *SkewDaily_i* and *KurtDdaily_i* suggests a scenario where promotion-induced reviews enter the review community in a larger volume at the higher speed than organic reviews after the FAD promotion ceases.

5. Empirical analysis

5.1. Exploratory analysis

To investigate the sales impact of price rebound and the relative importance of organic and promotion-induced reviews, we first explore the data descriptively. In Fig. 1, we look into the distribution of average sales of all 34 apps. We create Fig. 2 to illustrate the average daily number of reviews since Day 2 (Fig. 2a) and their average rating since Day 1 (FAD promotion day) (Fig. 2b).

It is interesting to observe a complex temporal trend in sales during post-promotion in Fig. 1. Fig. 1a) plots the sales rank over dates. Please note a *larger* value of sales rank indicates a *lower* amount of app sales. To be more intuitive, Fig. 1b) adopts the vertical axis as the negative value of log transformed sales rank. As mentioned early, we infer the sales by the negative log-linear relationship between sales and sale rank. We observe that sales have a sharp increase on the second day of post-promotion (Day 3) and turn to a downward trend in the next four days (Day 4 ~ Day 7), followed by a relatively stable trend at the end. This echoes

Table 3
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>SalesRank_{i,t}</i> (1)	1	-0.10	-0.03	-0.02	0.02	-0.02	-0.05
<i>NumReviews_{i,t}</i> (2)		1	0.14	0.33	-0.21	-0.11	0.41
<i>AppPrice_{i,t}</i> (3)			1	-0.05	0.13	-0.14	0.21
<i>AverageRating_{i,t}</i> (4)				1	-0.87	0.18	-0.04
<i>VarianceRating_{i,t}</i> (5)					1	-0.10	0.17
<i>Age_{i,t}</i> (6)						1	-0.41
<i>AppSize_{i,t}</i> (7)							1

Table 4
Skewness and kurtosis of daily number of reviews.

	Min	Max	Mean	STD
<i>SkewDaily_i</i>	0.31	2.83	1.82	0.72
<i>KurtDdaily_i</i>	-1.55	8.24	3.40	3.13

the intricate mechanism underlying the impacts of FAD promotion on app sales. The boosted visibility by FAD promotion leads to more immediate app adoptions. This can explain the sharp sales increase on Day 3. However, as implied by H1, the zero-price offering can unexpectedly backfire to reduce customers' willingness to purchase apps once the promotion is no longer valid. We believe this effect accounts for the dip in the sales to some degree.

Fig. 2 offers some preliminary support to our H2. Fig. 2a supports that reviews flood into the review platform at the beginning of post-promotion, and gradually slow down to a stable level. This echoes our theory that the surged reviews received at early days of post promotion are likely generated by users of FAD promotion, i.e., promotion-induced reviews, contributing to the sharp increase of daily number of reviews on the second day in Fig. 2a. On the other hand, the flattened curve in the tail supports that organic reviews are accumulated in a much smaller volume at a slower and more stable generating speed. Fig. 2b also supports prior findings that organic reviews tend to be less positive, indicated by the drop in average rating over time during post promotion (Kim et al., 2019; Litvin & Sobel, 2018). This observed positive bias in promotion-induced reviews also supports the value of organic reviews.

This exploratory analysis presents initial evidence consistent with our hypotheses and underlying theories. We will continue with a regression model for a more rigorous analysis in the following sub-section.

5.2. Regression model and results

To statistically test our hypotheses, we construct the following panel-data econometric model with two-way fixed effects:

$$-\ln(\text{SalesRank}_{i,t}) = \beta_0 + \beta_1 * \text{PriceRebound}_{i,t} + \beta_2 \text{SkewDaily}_i + \beta_3 \text{KurtDaily}_i + \beta_x \text{ControlX}_{i,t} + \mu_i + \rho_t + \varepsilon_{i,t}$$

where *ControlX_{i,t}* is a 1*6 control variable matrix that includes *Ln (NumberReviews_{i,t})*, *AverageRating_{i,t}*, *VarianceRating_{i,t}*, *Day_{i,t}*, *Age_{i,t}*, and *AppSize_{i,t}*, and β_x is a 6*1 coefficient matrix. We include app-fixed effects μ_i and time-fixed effects ρ_t to control for time-invariant app heterogeneity, such as app's idiosyncratic characteristics and intrinsic quality, and other omitted time-variant variables, such as market demand shocks, respectively (Duan et al., 2008). By doing so, we can ensure that the identified relationships hold regardless of the app difference and temporal trend.

As explained earlier, we use $-\ln(\text{SalesRank}_{i,t})$ as the dependent variable to proxy the log value of Amazon sales rank of product *i* at day *t*. Given the negative log linear relationship between the sales rank and sales, this model can estimate the sales impact of our key independent variables. We first include the difference of current app price and the app price on the date of FAD promotion, *PriceRebound_{i,t}*, to test H1. We notice that a few apps were off the direct spotlight post-promotion, however, still offer zero price for another one or two days. This gives the model enough data variation to estimate the coefficient on this term (β_1). Specifically, H1 suggests a negative coefficient (β_1) on price rebound that a larger price rebound hurts app sales to a greater degree.

To test H2, we include *SkewDaily_i* and *KurtDaily_i* to capture the relative importance of organic reviews and promotion-induced reviews. As discussed beforehand, greater *SkewDaily_i* and *KurtDdaily_i* capture a larger volume of promotion-induced reviews generated at a higher speed than organic reviews during early days of post FAD promotion. Specifically, an increase in *SkewDaily_i* indicates a more right skewed distribution of daily number of reviews during the post-promotion period. This implies that promotion-induced user reviews occur during early post-promotion as

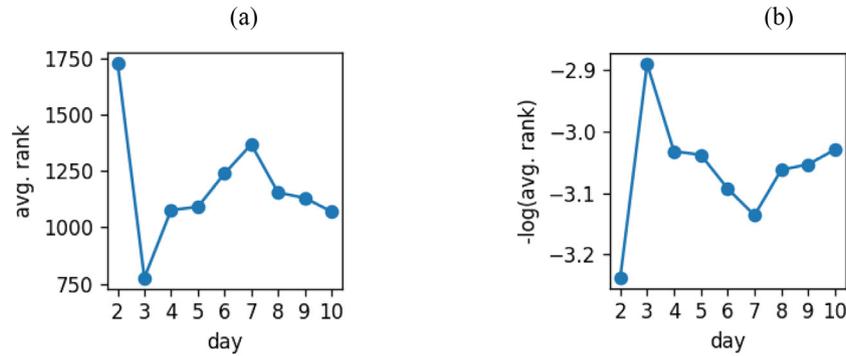


Fig. 1. Post-promotion average sales rank.

compared to organic reviews. An increase in $KurtDaily_i$ indicates a sharper skewness of this distribution, capturing the velocity at which the incoming promotion-induced user reviews are generated. As a result, H2 would suggest both negative coefficients on those two terms on $SkewDaily_i$ (β_2) and $KurtDaily_i$ (β_3). Given the total volume of user reviews being controlled for by $Ln(NumberOfReviews_{i,t})$ in the control variable matrix, H2 is conditional on the total volume of eWOM.

Following previous studies, we also include several control variables. We add $NumberOfReviews_{i,t}$ with a log transformation ($Ln(NumberOfReviews_{i,t})$) to represent the total number of user reviews the app i receives by week t . It controls for the impact of high visibility caused by the total number of user reviews (Liu, 2006). The underlying argument is that if there are more customers talking about the product online, more likely others would also notice it in online market, regardless of whether the conversation is incentivized or organic. Average review rating and the variance of ratings for the app, $AverageRating_{i,t}$ and $VarianceRating_{i,t}$, are also included to control for the effect of signaling product quality from review ratings (Zhu & Zhang, 2010). $Day_{i,t}$ measures the number of days since the FAD promotion. In addition, to control for the product diffusion process, we followed the literature to include product age $Age_{i,t}$ (Duan, Gu, & Whinston, 2009). $AppSize_{i,t}$ is also adopted to control for the potential effect of app size on customers' download decisions.

We run the above regression model towards our panel data set using Generalized Linear Model with two-way fixed effects. The estimation results are summarized in Table 5.

We also checked the potential endogeneity issue by Hausman test. The result rejects the possibility that there is a correlation between independent variables with the error term. Therefore, we feel confident about the robustness of the above estimation results.

As expected, the coefficient on $PriceRebound_{i,t}$ is significantly negative, supporting H1. This implies that returning to original price has a negative impact on app sales. We also find significantly negative coefficients on both $SkewDaily_i$ and $KurtDdaily_i$, supporting H2. This provides evidence that more positive value of skewness and kurtosis of daily number of post-

promotion reviews, which indicates a more right-skewed and sharper-topped distribution, can lead to lower post-promotion app sales. In other words, it is less beneficial to app sales when promotion-induced reviews are created in a larger volume at a higher velocity than organic reviews are, conditional on total number of reviews. In terms of control variables, we also find that their coefficients are all reasonable in our context, being consistent with prior findings.

6. Conclusions and future research

In this study, we investigate a digital marketing strategy, Amazon's FAD promotion, with a focus on the post-promotion period. Our exploratory analysis confirms that app sales benefit from FAD promotion during the first two days following the promotion event, however, sales go down subsequently due to the price rebound as well as promotion-induced reviews being relatively less influential. As with many other marketing strategies, we show that, in addition to the shining side of attracting new customers and user conversations, FAD also has its dull side that app developers should be mindful of and not take lightly.

Our work contributes to the literature in eWOM and digital marketing in three aspects. To our best knowledge, this study is among the first to investigate the post-promotion effect of a FAD marketing strategy. FAD promotion combines the features of free sampling and sponsorship as a unique way to promote the product. Our findings show the potential adverse effects that result from such promotion. This raises the importance of investigating the full spectrum of a new digital marketing strategy beyond the in-promotion period. In addition, our work extends the research on digital free sampling, particularly these on zero-price effects (Lin et al., 2013; Niemand et al., 2019). Prior works in this line of research focus on the benefits of free samples. We instead find that the removal of zero-price offering hurts app sales due to several underlying reasons. These reasons include customer's default expectation of apps being free, customer's unhappy emotion related with the app price's return to the normal, and customer's perceived net loss by observing the increased price, which were introduced

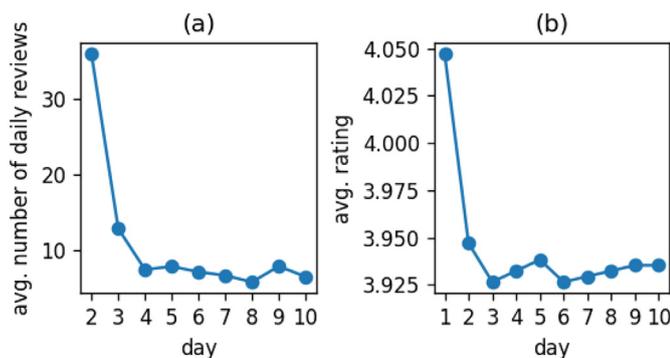


Fig. 2. Post-promotion user reviews.

Table 5
Regression estimation results.

	Mean	S.D.
$PriceRebound_{i,t}$	-0.40***	0.06
$SkewDaily_i$	-0.19*	0.11
$KurtDdaily_i$	-0.09**	0.05
$Ln(NumberOfReviews_{i,t})$	0.59***	0.08
$AverageRating_{i,t}$	2.06***	0.40
$VarianceRating_{i,t}$	1.17***	0.30
$Day_{i,t}$	-0.11*	0.03
$Age_{i,t}$	-0.0004***	0.0002
$AppSize_{i,t}$	0.01***	0.002
$R^2 = 0.45$		

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

by the FAD promotion. Third, our empirical results on post-promotion reviews also complements prior works on eWOM and, in particular, on non-organic reviews (Ballantine Paul & Au Yeung, 2015) by introducing two unique review measures: relative review volume and relative review velocity. As Sharma and Pandey (2011) pointed out in their comprehensive overview of eWOM in the digital platform, there is a need to identify useful eWOM measures to evaluate the eWOM strategy. Our proposed measures can help future research on differentiating organic reviews vs. non-organic reviews.

Our findings are helpful to practitioners in the following ways. First, our results alert the marketers of the risks of adopting a new marketing strategy, even if this strategy is built upon well-established practices. FAD is built upon the ideas of digital free sampling and sponsorship. However, such combination introduced the withdrawal of the zero-price offering, which hurts customer attitudes towards the product. We suggest firms carefully evaluate during and post promotion for a full picture of the pros and cons of the designed new strategy. Second, our results highlight the delicacy of “grassroots marketing” in the sense that the approach to solicit eWOM needs to be carefully designed in the distribution of digital experience products, e.g., apps (Sharma & Pandey, 2011). Using the temporary zero-price offering to generate a large volume of user reviews comes at a price. Once the price returns to the normal, our findings show that app downloads are negatively affected by the price increase during the post-promotion period. In addition, we also suggest app developers and platforms be mindful about the differential value of user conversations solicited through different approaches. Our results show that promotion-induced reviews hurt sales if they overpower the organic reviews (given everything else being equal). Therefore, practitioners are better off to explore ways to allow users to provide reviews at a gradual and steady pace.

Our paper inevitably has some limitations. It is noticeable that currently Amazon does not offer FAD anymore. Amazon replaced FAD promotion on August 26, 2015 with an expanded version, Amazon Underground (Singleton, 2015). Instead of promoting one single app for 24 hours with zero price, Amazon Underground offered hundreds of paid apps free of charge without time limitation (Singleton, 2015). Its revenue model is completely different from Amazon Appstore's. In Underground, Amazon pays the app developers by customer's time usage of the app and collects revenues mainly through displaying ads posted on the Amazon Underground downloading page (Singleton, 2015). The Underground platform lasted for about four years. It would be interesting to continue this research by using web-archived data from both Amazon Underground and Amazon Appstore. The high visibility resulting from the free offering at Underground can be less significant as compared to FAD, however, it is reasonable to expect its existence. After all, those hundreds of apps at Amazon Underground only account for a small portion of the available Android apps at Amazon Appstore. The effect of price rebound can be examined at Appstore by comparing the app's sales before and after it joins the Underground. The possibility of cannibalizing demands at the Appstore is worth looking into as well. On the other hand, the comparison between promotion-induced reviews and organic reviews becomes easier to implement in terms of data preparation, because now they are clearly differentiated by two distinct hosting platforms. In addition, variations of FAD strategies on other platforms are also worth exploring, e.g., Google Play's Free App of the Week in 2017 (Protalinski, 2017). It is not clear to what extent the removal of zero price and the flood of promotion-induced reviews would affect app sales in this scenario with a longer promotion period. It would be interesting to empirically test these relationships during the Free App of the Week program time.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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