1-2016

Experience Me! The Impact of Content Sampling Strategies on the Marketing of Digital Entertainment Goods

Ai Phuong HOANG
Singapore Management University, aphoang.2013@phdis.smu.edu.sg

Robert J. KAUFFMAN
Singapore Management University, rkauffman@smu.edu.sg

DOI: https://doi.org/10.1109/HICSS.2016.589

Experience Me! The Impact of Content Sampling Strategies on the Marketing of Digital Entertainment Goods

Ai Phuong Hoang
Singapore Management University
aphoang.2013@phdis.smu.edu.sg

Robert J. Kauffman
Singapore Management University
rkauffman@smu.edu.sg

Abstract

Product sampling allows consumers to try out a small portion of a product for free. Uncertainty associated with consumption of information goods makes sampling useful for digital entertainment providers. Firms offer some programming for free to attract consumers to purchase a series of programs. We explore the effectiveness of content sampling for information goods using a dataset containing more than 17 million free previews and purchase observations on households from a digital entertainment firm that offers video-on-demand (VoD). Based on theories related to product sampling and information goods, we analyze the relationship between free previews and VoD purchases for series dramas. Households with premium subscription packages show more interest in VoD, which implies higher utility for TV viewing. We also explore household sampling and purchasing patterns for VoD series dramas. Implementation of sampling plays an important role in stimulating more purchases, but in different and more nuanced ways than we expected.

1. Introduction

Advanced IT makes it possible for firms to market and sell information goods directly to consumers. In the digital entertainment industry, for example, service providers can offer any television program on demand by the viewers. *Video-on-demand* (VoD) services are a significant source of revenue for digital entertainment and telecom firms [18]. Markets and Markets [31] anticipates the VoD market to grow from US$21.08 million in 2013 to US$45.25 billion in 2018, at a cumulative annual growth rate (CAGR) of 16.5%. The report suggests that TV has become a pull industry: consumers are "pulling" the content they want. Viewers search for programs that are delivered anytime, anywhere that fit their preferences.

The most profitable services among current VoD offerings are *series dramas*. A series drama consists of ten, twenty or thirty episodes. By bundling these episodes together to offer them as one series, firms sell more programming with a higher margin [4]. The dramas garner strong demand from niche viewers.

A similar challenge for firms that offer digital goods, such as entertainment programming, is the high level of uncertainty associated with who will consume these goods. The quality of experience goods can only be realized after they are used [30, 40] and the quality of a TV program is known only after it has been watched. To overcome this challenge, different forms of sampling strategies have been used intensively across industries for information and experience goods. Program production companies make short trailers available to signal content quality. Apple iTunes offers 1.5-minute samples of songs it sells, for example. Other digital entertainment firms implement marketing strategies involving free viewing to stimulate purchases [11]. For series dramas, viewers can sample the first episode before making a purchase decision. Although sampling strategies are known to help generate sales for physical products, the impact of such strategies on the sales of digital goods is not well understood, especially for new VoD offerings.

Current literature on sampling strategies for information and experience goods often focuses on online music and software industries. These studies investigated the determinants of consumer decision-making and examined the consumption of such goods. We extend this literature by addressing the impact of sample content on purchases in the context of VoD market for series dramas. Once viewers subscribe, they spend hours watching it. While on-demand series bring higher profit margin for firms, they may cannibalize current viewers from other TV channels. Series dramas are a unique context that allows us to explore the magnitude of impact that free viewing has on the number of purchases.

Our purpose is to examine the effect of sampling strategies for digital goods on consumer purchase decision-making, especially in the VoD market. We observe how households sample and purchase VoD dramas, giving the households' current subscription packages. We ask: (1) What are the impacts of free previews on a household's likelihood of making a

VoD purchase? (2) To what extent do these free previews affect the number of household VoD purchases? (3) How does a household's current subscription package affect its VoD purchases?

2. Theoretical Background

The relevant literature to support our theory, modeling and methods covers three areas: (1) product sampling strategies; (2) consumer viewing behavior; and (3) consumer purchase behavior.

2.1. Product Sampling Strategies

Product sampling strategies have been widely studied across multiple disciplines. A dominant view in Marketing is that sampling supports high conversion rates and ROI for physical goods. Sampling can be more effective than traditional advertising [20, 27]. Jain et al. [14] modeled sampling in the diffusion of new products. It is an expensive strategy with limited market reach to traditional media though [7, 8]. Other [12] Consumer Behavior research explored the dual effects of sampling on the likelihood of purchases and consumers' formation of goodwill.

More attention has been given to sampling strategies for information and experience goods across the fields of Marketing and IS. This strategy has been employed in different industries as freemiums and versions in the software industry [7], and metering in the newspaper industry [11]. Film production companies release trailers and sneak peeks to attract viewers through these forms of sampling. Apple iTunes, an online music distributor, allows listeners to sample up to 90 seconds for all of its songs [38]. Content providers offer samples to disclose quality information to consumers to stimulate demand. Technologies also allow firms to reach a wider market with lower costs for digitalization and distribution [11].

2.2. Consumer Viewing Behavior

Audience satisfaction is defined as TV viewers' responses to a viewing experience that involves utility or fulfillment of some entertainment need [32]. Audience satisfaction is positively associated with *intention to purchase*. *Connectedness* is an antecedent of audience satisfaction [23]: it refers to the intensity of the relationship that a viewer develops with the characters and context while viewing TV programs [36]. As viewers spend more time watching portions of drama they connect to.

Variety-seeking behavior and *satiation* [25, 26] play a critical role in the consumption of hedonic goods. Consumers have a need for novelty, change, and complexity [39]. They like to explore a variety of programs and series dramas. Digital entertainment services providers offer a wide range of content to satisfy the needs of consumers, which stimulates more subscriptions for their programming.

People watch TV programs differently. Another study looks at interactions between viewing patterns and motivation, and identifies two types of *television viewers* [35]. One watches TV out of habit to pass time; the second seeks information and to learn.

2.3. Consumer Purchase Behavior

The *consumer-buying decision process* involves five steps: problem and need recognition; information search; evaluation of alternatives to meet this need; a purchase decision; and post-purchase behavior [6].

Searching for information related to experience goods can be challenging. Nelson [30] distinguished experience goods from search goods. All information goods are experience goods, including online music, movies, and books [15]. In contrast to search goods, the quality of experience goods is realized only after they have been used [30, 37]. A high level of uncertainty creates a higher perceived transaction cost, so imperfect information about the goods hinders consumers' willingness to pay. Consumers seek information to update their expectations and mitigate their risk. Moretti [28] showed that social learning and peer effects have positive impacts on consumption of movie sales. Firms, meanwhile, need to manage the impact of social contagion and signal quality information to consumers [5]. Sampling is a more active strategy for firms to signal product information to customers. It reduces consumer uncertainty [24], and increases the likelihood of purchases [29, 33, 34].

Consumers also evaluate relevant alternatives before purchasing. Purchases of digital goods involve more risk, given that consumers have a limited time and budget. So consumers need to acquire information on different alternatives to select the one that will maximize their utility.

3. Hypothesis Development

3.1. Free Previews and VoD Series Purchases

The dominant view in the literature considers viewing activity as a *gratification-seeking process* [22]. Viewers actively search for and watch the content that matches their preference. VoD services offer convenience and flexibility by allowing consumers to choose content they like and watch it anytime they want. The *purchase of a VoD drama* represents the granting of household access to the content over a given period of time, ranging from 30 to 75 days – depending on the number of shows in the drama.

VoD purchase decisions involve some issues though. First, VoD services can be expensive compared to other services that the service provider offers. A VoD series drama can cost anywhere from $3 to $60, payable on top of the current TV subscription packages. Second, consumers typically buy the dramas that are enjoyable to watch, rather than to fulfill any specific information needs. But it may be hard for consumers to judge whether a given drama is worth purchasing.

Consumers actively seek relevant product information before making purchase decisions, especially when there may be financial consequences [3]. Quality signals are critical for experience goods as much as it is for physical goods in stimulating more purchases [8, 24]. Service providers typically offer consumers the first episodes of all of their series dramas for free to reduce product uncertainty and signal product quality. Viewing a small portion of a drama gives consumers more information and encourages them to purchase it, if it matches their preferences. By sampling many dramas, consumers can find a suitable one, which may increase their likelihood of purchase.

There are potential downsides of free previews. *Freebies* sometimes increase the difficulty for some consumers to decide whether purchasing items will be worthwhile [16]. They may interfere with the mechanism related to their intention to purchase. Unlimited access to a variety of free content also makes the programs less attractive to consumers [16]. Some consumers may be satisfied with the free episodes only, or some consumers may purchase the drama even if sampling was not provided. Though possible, these scenarios are not likely to be true for majority of consumers in the VoD setting. Consumers have many channels in their subscription packages, they will be unlikely to watch a free episode if they have no prior interest in it. Providers offer previews only as a sample of drama series, so free episodes should not be considered as purely free content. As the first episodes of the series, these episodes will closely link to subsequent episodes, which will encourage consumers to purchase the rest of the content.

Thus, sampling strategies are likely to have a positive impact on the purchase of VoD dramas. To wit:

- **Hypothesis 1 (Free Preview Sampling and Any Drama Purchases).** *The number of dramas a household samples has a positive effect on its likelihood to purchase any drama.*

We explore the relationship between sampling strategies and VoD purchases one step further. Since free previews are believe to increase the likelihood of consumer purchase, a service provider will be interested to know how many dramas households will buy in the presence of such sampling opportunities. To what extent do free previews stimulate additional purchases after a household has made its first purchase of a drama? The people in different households are likely to have different utility from TV viewing. They also have limited budgets for purchasing entertainment services. So understanding the optimal level of consumer purchases is important for providers.

Free previews encourage a diverse viewing experience. Consumers tend to sample a variety of dramas that have sample episodes available. For instance, a household that normally prefers comedy-related dramas may sample a crime-related drama and find it interesting. This variety-seeking behavior often results in more purchases across different types of series. Consumers may purchase more than one drama.

Series dramas are typically more expensive and longer than other programming. A 20-episode drama takes about 15 hours to finish watching, at around 45 minutes per episode. Thus, time and budget constraints may hinder subsequent VoD purchases. As a result, the impact of sampling strategies diminishes after the first purchase. We propose:

- **Hypothesis 2 (Free Preview Sampling and Number of Dramas Purchased).** *The number of dramas a household samples has a positive effect on the number of dramas it purchases.*

3.2. Subscription Purchase Effects

The typical contract term for paid TV services, in which households sign up for service packages that have different combinations of channels, is three months or more. In the most basic package, a household can choose from three groups of content from a number of primary groups, such as news shows, children's programs, and entertainment and educational shows. When signing up for a subscription, households also can add on channels that reflect their specific interests, such as sports, movies, fashions, or other branded channels (Discovery, Disney, History, etc.). Monthly subscription fees will reflect the number of channels as well as the type of programming accessible to households. A premium package with more channels will be more expensive, of course.

The subscription package that a household selects will have different implications for its VoD purchases. One direct implication is the cannibalization of demand. Given the fixed amount of time in a day, any time-consuming activity constrains other activities [1]. Liebowitz and Zentner [21] empirically show the negative impact of Internet consumption on television viewing. So households that spend more time watching a set of preferred channels have less time left to view other programming, such as VoD dramas. Furthermore, households with a premium package

will have many available channels to choose from, and probably will not care very much about VoD content. This suggests that households with comprehensive subscription packages will be less likely to purchase VoD programs. At the same time, the household's current subscription packages also may reveal its expected level of utility from TV viewing and its willingness-to-pay. For instance, smaller households with fewer members or those who do not have much time for TV viewing may just want basic and inexpensive packages. By the same token, larger households may want more comprehensive packages to meet the needs of all of their family members. If TV viewing is the main form of entertainment for the household, then subscribing to more channels will be appropriate. These households will be more likely to try out free episodes, and express a willingness-to-pay for VoD dramas.

Add-on channels reveal a household's viewing preference more closely, thus they may reduce the demand for dramas. When households already have add-on channels that match their viewing preferences, other content will be less desirable for them. On the contrary, these households express a higher willingness-to-pay for special content, they will be most likely to purchase more VoD dramas if the dramas trigger viewing interests.

Though free sampling may cannibalize some demand, we expect this to be of minimal concern in this research context. Series dramas represent a specific form of digital entertainment, as the viewers have to watch the entire series for a complete viewing experience. With this in mind, we propose:

- **Hypothesis 3 (Number of Subscribed Channels)** *The number of channels a household subscribes to has a positive effect on the number of dramas that the household purchases.*
- **Hypothesis 4 (The Number of Add-On Channels).** *The number of add-on channels that a household subscribes to has a positive effect on the number of dramas it purchases.*

4. Research Setting and Data

This research was made possible through a partnership with a large digital entertainment firm. The data pertain to household-level VoD sampling, purchasing, and viewing activities for one month between September 30 and October 30, 2011. The data include 17+ million VoD viewing sessions for more than 100,000+ households. There were no public holidays or special events during that time period that might have influenced household viewing activities in ways that would affect our use of the data for our present purpose. We observed no abnormal viewing peaks, and October is free of seasonal effects. The data are sufficient for the research questions.

There were 73 series dramas offered during this period, accounting for 26,435 free previews and 1,134 purchase records across 13,120 households. We retrieved household subscription information for the independent variables, specifically the number of subscribed channels and add-on channels. Some households purchased various programming at different points during the research period, which caused difficulties with being able to obtain a full dataset for all the targeted households. We also needed to obtain demographic information of the households, such as dwelling type, gender and age to serve as control variables. We encountered severe missing value issues for these demographic variables though, as most households did not provide this information when they signed their contracts. As a result, we made choices about the *data rectangles* that we used: either wide and short rectangles with the largest number of variables (columns) but fewer households (rows), or narrow but tall rectangles with a smaller number of variables but more households. We decided to include the subscription information and exclude the demographic information. Our final dataset for estimation has 7,932 households with complete subscription information. Descriptive statistics are in Table 1.

Table 1. Descriptive statistics

N = 7,932	MIN	MED	MEAN	MAX	SD
DramaPurchases	0	0	0.11	7	0.43
FreePreviews	0	1	2.18	26	2.16
SubscribedChannels	0	14	14.70	41	6.25
AddOnChannels	0	2	3.16	25	3.04

The dependent variable for the gogistic model is a binary variable: households with more than one VoD purchase is 1 and 0 otherwise. The dependent variable for the count data models, *DramaPurchases*, is the number of VoD series dramas a household purchased during the study period. *FreePreviews* refers to the number of dramas that the household sampled. *SubscribedChannels* captures how many channels the household subscribed to, whereas *AddOnChannels* refers to specific channels that the household from. A sample correlation matrix is showed in Table 2.

Table 2. Variable correlations: Censored Sample

VARIABLES	1	2	3	4
1. *DramaPurchases*	1.000			
2. *FreePreviews*	0.146	1.000		
3. *SubscribedChannels*	0.104	-0.028	1.000	
4. *AddOnChannels*	0.122	-0.014	0.648	1.000

Note. The least correlated variables are *FreePreviews* and *AddOnChannels* (-0.014), and the most correlated ones are *SubscribedChannels* and *AddOnChannels* (0.648).

The highest correlation is between *SubscribedChannels* and *AddOnChannels* at 0.648, which is still within the traditional range of acceptable correlation. This is intuitive. A household that subscribed to a premium package with more channels, is more likely to add on channels. *SubscribedChannels* and *AddOnChannels* have different implications on VoD *Drama Purchases* though. The results of the variance inflation factor (VIF) test show no problems with multicolinearity.[1]

5. Empirical Models

We now will describe the econometric models that are used to test our proposed hypotheses.

5.1. Logistic Regression Model

For households, we can observe the number of channels currently subscribed, the times households have sampled or purchased VoD drama series, and their other contracted services. The logistic model is used to predict a dichotomous (0,1) outcome [13]. That is, the binary response of whether a household purchases VoD series. The regression coefficients are estimated using maximum likelihood estimation.

5.2. Baseline Model for Count Data

We use a baseline model for the relationship between the number of *DramaPurchases* and other factors, such as the number of *FreePreviews*, and the number of *SubscribedChannels* and *AddOnChannels*.

$$DramaPurchases = f(FreePreviews, SubscribedChannels, AddOnChannels; Controls)$$

Letting i denote the household level, we estimate:

$$DramaPurchases_i = \beta_0 + \beta_1 FreePreviews_i + \beta_2 SubscribedChannels_i + \beta_3 AddOnChannels_i + \varepsilon_i$$

The variable of interest is VoD *DramaPurchases*. If a household did not purchase any dramas, then this variable is left-censored at 0. The censored sample is still representative of the population since observations at the limit are included; censoring makes ordinary least squares (OLS) estimates econometrically inconsistent though [9]. Due to time and budget constraints, we do not expect to see the households make many purchases; and the observed maximum is just 7 dramas. Thus, the count of the number of purchases is either 0 or a small positive number.

5.3. Count Data Models

We will apply and assess various count data models for the estimation of our explanatory model and the related data. *Count data models* restrict the dependent variable to non-negative integer values and take into account the relationship between the mean and variance of the distribution that is used to characterize the dependent variable [17].

Poisson regression. The *Poisson regression model* is the most well-known of the discrete regression models for count data. The events to be estimated are independent of one another [17]. The advantage of this model is the use of the Poisson distribution, which does not impose any restrictions on the values of the dependent or independent variables. It has a limitation in practical application though: The underlying distribution of the dependent variable must exhibit equal means and variances. As a result, we use this model as a baseline for our count data models.

Negative binomial model. Our dataset has some characteristics that undermine the Poisson model. We observe a sparse dependent variable matrix, which is common in purchase conversion research settings. The majority of households did not purchase any dramas; and, at 91.3%, this is a larger proportion than what we would see in a normal distribution. When the conditional variance of the dependent variable exceeds the conditional mean, the estimated values of the parameters will tend to be greater than what would be predicted, which is *over-dispersion*. As a result, the standard errors of the parameters estimated in the Poisson regression model will be underestimated [17]. *Negative binomial regression* generalizes Poisson regression and handles this issue. It has an extra parameter to model over-dispersed data. The confidence intervals for a negative binomial are narrower compared to a Poisson regression model's.

Zero-inflated negative binomial and hurdle models. Poisson regression also assumes that the 0s and non-0s come from the same *data-generating process* [2]. This doesn't hold true in our setting though. *Zero-inflated and hurdle models* relax this assumption. The *hurdle model* assumes there is a Bernoulli probability that governs the binary outcome for the count variable having a 0 or *positive realization*. Once the hurdle is crossed, and a positive realization occurs, the conditional distribution of the positive outcomes is governed by a *truncated-at-zero count data model* [10, 14]. With the *zero-inflated models*, the response variable is modeled as a mixture of a Bernoulli distribution and a Poisson distribution [10]. The choice of models is based on prior knowledge of the cause of the excess 0s.

Relative to the price of the drama series offerings, which can be expensive in comparison to other services, households have to decide what they are will-

[1] The VIF values for *FreePreviews, SubscribedChannels* and *AddOnChannel* are 1.002, 2.251 and 2.252, respectively.

ing to pay for. A *no-purchase decision* may result from two different processes. If a household does not have money or time to watch the whole series, they will not purchase regardless of whether they watched the free previews. Yet, if a household has time and money, then we can describe their decision-making process as a *count process* influenced by the variable *FreePreviews*. The expected count for different values of k is a combination of the two processes:

$$\begin{aligned} &E\,(DramaPurchases = k) \\ &\quad = Prob\,(Household\ has\ no\ budget\ or\ no\ time) \cdot 0 \\ &\quad + Prob\,(Household\ has\ budget\ and\ time) \cdot E(y = k \mid \\ &\qquad Has\ budget\ and\ time) \end{aligned}$$

To account for the excess 0s that come from the two different processes, we use the *zero-inflated negative binomial regression* model. It has two parts: a *logit model* and a *negative binomial count model*. The logit part models the probability of excess 0s independently; that is, the probability of *DramaPurchases* = 0, due to the fact that households have neither budget nor time. These parts of the model do not need to use the same predictors; the estimated parameters of the factors do not need to be the same either. The probability density function [19] is: $\Pr(Y_i = y_i)$

$$= \begin{cases} \Phi + (1-\Phi)(1+k\mu_i)^{-k^{-1}} & y_i = 0 \\ (1-\Phi)\dfrac{\Gamma(y_i + k^{-1})}{y_i!\,\Gamma(k^{-1})}\dfrac{(k\mu_i)^{y_i}}{(1+k\mu_i)^{y_i+k^{-1}}} & y_i > 0 \end{cases}$$

with $E(y) = \mu_i(1 - \phi)$; and $Var(Y_i) = \mu_i(1 - \phi)\ (1 + k\mu_i + \mu_i)$, where μ_i and ϕ depend on the covariates, and $k \geq 0$is a scalar. When either ϕ or k is greater than 0, we have *over-dispersion*. When $\phi = 1$, the equation reduces to a negative binomial model, and when $k = 0$, it becomes a zero-inflated Poisson model.

6. Analysis Results

6.1. Logistic Regression Results

We present the logistic model's results first. The coefficient of the number of *FreePreviews* is positive and significant, supporting the Free Preview Sampling and Any Drama Purchased Hypothesis (H1). For one additional free preview that a household watches, the odds of purchasing VoD series increase by 12.8% (since the log odds of purchase increase by 0.12). The Appendix materials on Sampling and Purchasing patterns provide support for the positive causal relationship between free previews and purchases. Also the results from the logistic regression show a positive relationship between the number of *SubscribedChannels* and *AddOnChannels* relative to the likelihood of purchase.

Table 3. Logistic regression results

Dependent Variables	Coef.	SE	z-Val.	p (>|z|)
Intercept	-3.377	0.117	-28.93	< 2E-16***
Free Previews	0.120	0.014	8.57	< 2E-16***
Subscribed Channels	0.025	0.008	3.08	2.06E-03***
AddOnChannels	0.093	0.015	6.19	5.91E-10***

Notes. Signif. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Null dev.: 4,706.9, 7,931 d.f.; res. rev.: 4,509.1, 7,928 d.f., AIC: 4,517.1.

6.2. Poisson and Negative Binomial Results

We present the Poisson model (baseline for count models), and negative binomial regression results.

Table 4. Poisson and Negative Binomial Results

Dependent Variables	Poisson		Negative Binomial	
	Coef. (Std. Err.)		Coef. (Std. Err.)	
Intercept	-3.226***	(0.094)	-3.393***	(0.018)
FreePreviews	0.137***	(0.008)	0.173***	(0.014)
Subscribed Channels	0.026***	(0.007)	0.029***	(0.008)
AddOnChannels	0.075***	(0.012)	0.084***	(0.015)

Notes: Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We discuss the results of. The coefficients of the number of *FreePreviews, SubscribedChannels* and *AddOnChannels* are positive and significant. These results support the Free Preview Sampling and Number of Dramas Purchased Hypothesis (H2). The coefficient for *FreePreviews* is 0.137, implying that the expected value of ln(*DramaPurchases*) for an additional free preview is 0.137. If a household were to watch one more free preview, its corresponding *incidence rate ratio* would be expected to increase by a factor of 1.147. That is, households with an additional free preview purchase dramas 14.7% more of the time. Likewise, the expected value of ln(*Drama Purchases*) for an additional channel and an add-on channel in a household are 0.026 and 0.075. The Number of Subscribed Channels Hypothesis (H3) and the Number of Add-On Channels Hypothesis (H4) are also supported.

The coefficient estimates from the negative binomial regression support all the hypotheses and are consistent with the results from the Poisson regression. As expected, these coefficients are slightly larger than those from the Poisson regression (0.173 > 0.137, 0.029 > 0.026, and 0.084 > 0.75).

6.3. Empirical Model Assumptions

The Poisson model is actually nested in the negative binomial model. It relaxes the assumption in the Poisson model that the conditional variance is equal to the conditional mean, by estimating one extra vari-

able. We use a *likelihood ratio test* to assess the null hypotheses and if the restriction implicit in the Poisson model is true. $\lambda = -2 \cdot (LL_{NegativeBinomial} - LL_{Poisson})$

For our data, the null of the Poisson restriction being appropriate was rejected in favor of the negative binomial regression. This is based on the χ^2 test statistic = 353.60, which exceeds 2.71 with a *p*-value of less than 2.2e-16). The data are over-dispersed.

6.4. Negative / Zero-Inflated Models' Results

Next, we used the zero-inflated binomial regression model to estimate the data and account for the excess 0s that come from two different processes. The probability of 0s is modeled independently. In Table 5, we present results from the negative binomial regression (similar to Table 3), along with results from the zero-inflated negative binomial model.

Table 5. Results: Negative Binomial and Zero-Inflated Negative Binomial Models

VARIABLES	NEG. BIN.	ZERO-INFL. NEG. BIN. Count	ZERO-INFL. NEG. BIN. Logit
	Coef. (SE)	Coef. (SE)	Coef. (SE)
Intercept	-3.393*** (0.018)	-2.277*** (0.298)	1.192** (0.437)
FreePreviews	0.173*** (0.014)	0.194*** (0.021)	0.034 (0.030)
SubscribedChannels	0.029*** (0.008)	0.011 (0.012)	-0.040 (0.024)
AddOnChannels	0.084*** (0.015)	0.018 (0.022)	-0.277*** (0.075)
Ln(θ)		-0.350 (0.260)	
Notes. Signif. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; $\theta = 0.703$.			

In the count part of the zero-inflated negative binomial regression, the impact of free previews on VoD purchases is positive and statistically significant. The expected change in log (Purchases) for a one additional free preview is 0.194. That is, an additional free preview is associated with a 21% increase in drama purchases. This impact of a free preview here is stronger compared to the results from the Poisson or negative binomial models. The coefficients for *SubscribedChannels* and *AddOnChannels* were not significant though.

The logit part of the regression models the excess 0s independently. The log odds of excess 0s decrease by 0.277 for every additional add-on channel that a household has. In other words, the more add-on channels the household has, the less likely that the 0s would be due to the time and budget constraints. *AddOnChannels* signals a household's intention to purchase VoD programs.

6.5. Model Comparison and Robustness

Zero-inflated, negative binomial, and null models. To see whether the zero-inflated negative binomial model fits the data significantly better than the null intercept-only model, we compare them using a χ^2 test for the difference of the log likelihoods.

$\lambda = -2 \cdot (LL_{Zero\text{-}InflatedNegativeBinomial} - LL_{NullModel})$

The associated χ^2 value is 277.29, which supports the argument that the zero-inflated negative binomial model is statistically significant.

Zero-inflated negative binomial, and negative binomial models. The model output above does not indicate whether the zero-inflated model is an improvement over a standard negative binomial regression. To assess this, we performed a *Vuong closeness test* that tells us whether the two models are indistinguishable.[2] We reject the null hypothesis that the two models are equally close to the true data-generating process (test statistic = 3.28). So the zero-inflated negative binomial regression is better than a standard negative binomial regression in this setting.

Data rectangles and research questions. An important aspect of empirical research with consumer data is to obtain as deep an understanding of consumer behavior as the data will allow. We used multiple data sources to bring together subscription and demographic information on households for this study. Not all of the data we needed were available though. So we had to make choices about the usable *data rectangles.* We considered whether to use many rows of observations and fewer columns of variables (a tall but narrow rectangle), or a few more columns of variables by many fewer rows of data (a shorter but wider rectangle) to address our research objectives.

To observe the impact of sampling strategies, we used data involving household subscription and demographic information: a shorter and wider data rectangle. This subset of the data contains 7,932 households with complete subscription information, out of 13,120 households in the original dataset. To explore the viewing and purchase patterns of the households, we can use viewing and purchase records of 13,120 households (a taller and narrower data rectangle). Our choice reflects our effort to balance the height and width of the data rectangles, as a basis for providing meaningful results.

Sequence of sampling and purchasing. A concern with the research approach might be that we did not take in account the sequence of sampling and purchase records. Consider the extreme scenario in

[2] The *Vuong test for non-nested models* is used to test for zero-inflation in the zero-inflated negative binomial over the standard model. There is the possibility of potential misuses [41].

which households made purchases when the study period began, and thus any subsequent free previews ought to play no role in stimulating series purchases.

This is an important issue, but it is not our main concern. We aim to explore the overall effectiveness of the sampling strategies and the level of analysis of the household level during the study period. At this stage, we have not sought to focus on the impact of free previews for the sales of a particular drama. That can be a future research direction.

7. Conclusion

Academics and practitioners alike emphasize the impact of sampling strategies for physical as well as information goods. The market for series drama VoDs offers a unique context to assess the impact of free viewing on purchases, but also the magnitude of the impact. We have shown that the implementation of sampling plays an important role in enhancing consumer engagement and stimulating more purchases, but in more nuanced ways than expected.

7.1. Contributions and Discussion

Our primary purpose has been to investigate the impact of sampling strategies in the video-on-demand market, where series dramas are offered at relatively high prices to consumers. We examined the impact of households' preview sessions on the likelihood and the number of purchases.

The results suggest that *FreePreviews* have a positive impact on the likelihood of *Purchase* as well as the number of *DramaPurchases*. Households that subscribed to premium packages (*SubscribedChannels*) and more specific channels (*AddOnChannels*) still show an interest in VoD offerings. These households will obtain a higher level of utility from TV viewing, and a correspondingly higher willingness-to-pay for special programming. Also, *DramaPurchases* are not constrained by a household's current subscription. After accounting for the majority of "no purchase" decisions in our sample, we showed that the more *AddOnChannels* a household has, the more likely that it has time and budget for VoD programs.

We are the first to provide empirical support for the effectiveness of the content sampling strategies that are used for VoD series drama purchases. An additional free preview is associated with a 21% increase in drama purchases. Series dramas are niche products that are a major source of revenue for service providers. Our results produced useful insights for the marketing of digital entertainment goods. Sampling strategies help to reduce marketing costs and increase marketing performance. From the firms' perspective, the next step is to design and implement a value-maximizing bundle that includes freemiums. Firms also can adjust their strategies to stimulate more purchases from households that have only the basic subscription packages.

7.2. Limitations

We note the following limitation with the dataset used in this study. First, with a one-month dataset, we only have 73 data points at the drama level. Such limited data prevent us from exploring the impact of free previews on sales for a particular drama through time. Second, all viewing timestamps (start time and end time) are recorded in time blocks. We do not know the exact sampling and viewing durations, thus we cannot make any conclusion regarding the absolute viewing time. These limitations provide the impetus for future research though.

Interdisciplinary research is called for, to do more to address the implementation of the freemium model for experience goods. What insights can service providers gain from observing how consumers watch the paid channels and sample the free episodes? How useful are consumers' viewing and sampling patterns in predicting VoD purchases? Escapist viewers watch TV out of habit and to pass time. As they do not focus on the content, they are less likely to be influenced by the free episodes. On the contrary, if viewers watch TV for information and entertainment purposes, they are more responsive to the sampling content and more likely to make purchase decision.

How do the two types of viewers differ in terms of their sampling frequencies and patterns? Analysis of viewing sequences and durations are likely to provide additional insights on how consumers interact with the implementation of content sampling. We hope to further pursue this research direction.[3]

8. References

[1] Becker, G.S. A theory of the allocation of time. *Econ. J.*, 75(299), 1965, 493-517.

[2] Cragg, J.G. Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometr. Soc.*, 1971, 829-844.

[3] **Acknowledgment and data disclaimer.** This research was conducted with the participation of under a binding non-disclosure agreement. The data used to create the results have been anonymized. Identities of individual households and account holders cannot be traced back through the data we have discussed and analyzed. This research was supported by the Singapore National Research Foundation under its International Research Centre @ Singapore Funding Initiative and administered by the IDM Programme Office, Media Development Authority (MDA).

[3] De Matos, M., Ferreira, P., Smith, M.D., Telang, R. Culling the herding: using real world randomized experiments to measure social bias with known costly goods. *Mgmt. Sci.,* 2015, in press.
[4] Dennis, D.M., Gray, D.M. An episode-by-episode examination: what drives television-viewer behavior – digging down into audience satisfaction with television dramas. *J. Adv. Res.*, 53(2), 2013, 166-174.
[5] Dimoka, A., Hong, Y., Pavlou, P.A. On product uncertainty in online markets: theory and evidence. *MIS Qrly.*, 36(2), 2012, 395-426.
[6] Engel, J.F., Blackwell, R.D., Miniard, P.W. *Consumer Behavior*. Fort Worth, TX: Dryden Press, 1995.
[7] Faugère, C., Kumar, G.T. Designing free software samples: a game theoretic approach. *Info. Tech. Mgmt.*, 8(4), 2007, 263-278.
[8] Freedman, A.M. Use of free product samples wins new favor as sales tool. *Wall St. J.,* Aug. 28, 1986, 19.
[9] Greene, W.H. *Econometric Analysis*. London, UK: Pearson, 2012.
[10] Gurmu, S., Trivedi, P.K. Excess zeros in count models for recreational trips. *Amer. Stat Assoc.*, 14(4), 1996, 469-477.
[11] Halbheer, D., Stahl, F., Koenigsberg, O., Lehmann, D.R. Choosing a digital content strategy: how much should be free? *Intl. J. Res. Mktg.*, 31, 2014, 192-206.
[12] Heiman, A., McWilliams, B., Shen, Z., Zilberman, D. Learning and forgetting: modeling optimal product sampling over time. *Mgmt. Sci.*, 47(4), 2001, 532-546.
[13] Hosmer, Jr., D. W., Lemeshow, S., Sturdivant, R.X. *Applied Logistic Regression*. Hoboken, NJ: Wiley.
[14] Jain, D., Mahajan, V., Muller, E. An approach for determining optimal product sampling for the diffusion of a new product. *J. Prod. Innov. Mgmt.*,12(2), 1995, 124-135.
[15] Jones, R., Mendelson, H. Information goods vs. industrial goods: cost structure and competition. *Mgmt. Sci.*, 57(1), 2011, 164-176.
[16] Kamins, M.A., Folkes, V.S., Fedorikhin, A. Promotional bundles and consumers' price judgments: when the best things in life are not free. *J. Cons. Res.*, 36(4), 2009, 660-670.
[17] Kauffman, R., Techatassanasoontorn, A., Wang, B. Event history, spatial analysis and count data methods for empirical research in information systems. *Inf. Tech. Mgmt.*, 13(3), 2012, 115-147.
[18] Lafayette, J. Threat becomes profit center as TV leverages technology. *Broadcast. Cab.*, 144, 2014, 16-16.
[19] Lawal, B. Zero-inflated count regression models with applications to some examples. *Qual. and Quant.*, 46(1), 2012, 19-38.
[20] Liebeskind, J., Rumelt, R.P. Markets for experience goods with performance uncertainty. *RAND J. Econ.*, 20(4), 1989, 601-621.
[21] Liebowitz, S.J., Zentner, A. Clash of the titans: does Internet use reduce television viewing? *Rev. Econ. Stat.*, 94(1), 2012, 234-245.
[22] Lin, C.A. Modeling the gratification-seeking process of TV viewing. *Hum. Comm. Res.*, 20, 1993, 224-244.
[23] Lu, X., Lo, H.P. Television audience satisfaction antecedents and consequences. *J. Adv. Res.*, 47(3), 2007, 354-363.
[24] Markopoulos, P.M., Clemons, E.K. Reducing buyers' uncertainty about taste-related product attributes. *J. Mgmt. Info. Sys.*, 30(2), 2013, 269-299.
[25] McAlister, L. Choosing multiple items from a product class. *J. Cons. Res.*, 6(3), 1979, 213-224.
[26] McAlister, L., Pessemier, E. Variety seeking behavior: an interdisciplinary review. *J. Cons. Res.* 9(3), 1982, 311-322.
[27] McGuinness, D., Gendall, P., Mathew, S. The effect of product sampling on product trial, purchase and conversion. *Intl. J. Adv.*, 11(1), 1992, 83-92.
[28] Moretti, E. Social learning and peer effects in consumption: evidence from movie sales. *Rev. Econ. Stud.*, 78(1), 2011, 356-393.
[29] Motes, W.H., Woodside, A.G. Purchase experiments of extra-ordinary and regular influence strategies using artificial and real brands. *J. Bus. Res.*, 53, 2001, 15-35.
[30] Nelson, P. Information and consumer behavior. *J. Pol. Econ.*, 78(2), 1970, 311-329.
[31] Newswire, P.R. Video on demand market worth $45.25 billion by 2018. December 6, 2013.
[32] Oliver, R.L. *Satisfaction: A Behavioral Perspective on the Consumer*. Armonk, NY: M.E. Sharpe, 2010.
[33] Peter, J.P., Nord, W.R. A clarification and extension of operant conditioning principles in marketing. *J. Mktg.*, 46(3), 1982, 102-107.
[34] Rothschild, M.L., Gaidis, W.C. Behavioral learning theory: its relevance to marketing and promotions. *J. Mktg.*, 45(2), 1981, 70-78.
[35] Rubin, A.M. Television uses and gratifications: the interactions of viewing patterns and motivations. *J. Broadcasting*, 27(1), 1983, 37-51.
[36] Russell, C.A., Norman, A.T., Heckler, S.E. The consumption of television programming: development and validation of the connectedness scale. *J. Cons Res.*, 31(1), 2004, 150-161.
[37] Shapiro, C., Varian, H.R. *Information Rules: A Strategic Guide to the Network Economy*. Boston, MA: Harvard Business School Press, 1999.
[38] Tu, Y., Lu, M.L. An exploratory study on the effectiveness of online digital music sampling. *AMA Winter Educ. Conf. Proc.*, 18, 2007, 386-386.
[39] Venkatesan, M. Cognitive consistency and novelty seeking. *Cons. Beh.: Theor. Sources*, 1973, 354-384.
[40] Wilde, L.L. Information costs, duration of search, and turnover: theory and applications. *J. Pol. Econ.*, 89(6), 1981, 1122.
[41] Wilson, P. The misuse of the Vuong test for non-nested models to test for zero-inflation. *Econ. Lett.*, 127(1), 2015, 51-53.

APPENDIX

Table A1. Sampling and Purchasing Patterns

Only a few studies have analyzed the interaction between how consumers sample and make purchases. Firms cannot observe consumer sampling behavior. Traditional data collection is costly and subject to bias. For experience goods, providers often keep records of where, when and how consumers watch sampled content. This aids their understanding of household behavior. We explore consumer sampling and purchasing patterns for VoD series dramas.

To strengthen our claim on the causal relationship between free previews and the likelihood of purchase, we observed household preview and purchase sessions with at least one purchase. We used household data without subscription information. There are 3,652 observations of 823 households that purchased 1,130 series within our one-month study period. Figure A1 shows the average number of free preview and purchase records by weekdays, and the portion of purchases that are stimulated by free previews.

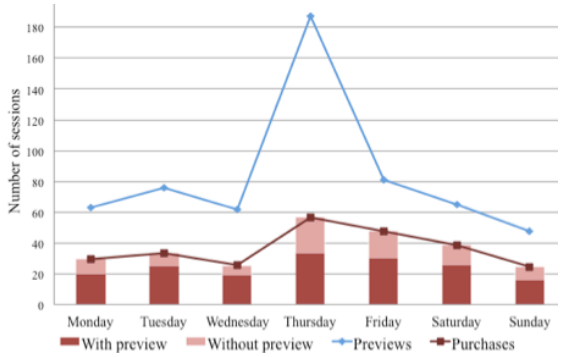

Figure A1. Average number of free previews and purchases, by day of the week

We observe similar sampling and purchasing patterns, except for the sampling peak on Thursday. This supports the positive relationship between free previews and purchases. Viewers watch the most free previews on Thursday, when high number of purchases occurs. Viewers show less interest in VoD toward the weekends; the average sampling and purchasing observations slowly decrease. The patterns suggest different stories (e.g., households search for and purchase dramas, to watch during the weekend).

The high number of free previews raises a question for service providers. How should they improve the conversion rate for VoD programs, as many households have shown an interest? The *rate of conversion* refers to the ratio of the number of purchases over the number of free previews.

We looked at the average number of purchases that are stimulated by free viewing. A purchase stimulated by a free preview occurs when a household purchases the drama that it has previewed. Consistent with our results that show the positive impact of free previews on VoD purchases, more than half of the purchases seem to be associated with free previews. Some households made their purchases without sampling the dramas though. These purchases may be influenced by outside information [3]. Establishing a understanding of the relative impacts of sampling strategies and outside sources of information will enable firms to design and implement effective marketing strategies.

Table A2. Poisson results

Dep. Var.	Coef.	SE	z-Val.	p (>|z|)
Intercept	-3.226	0.094	-34.36	< 2E-16***
Free Previews	0.137	0.008	16.67	< 2E-16***
Subscribed Channels	0.026	0.007	3.95	7.73E-05***
AddOnChannels	0.075	0.012	6.29	3.18E-10***

Notes. Signif. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Null dev.: 4,672.2, 7,931 d.f.; res. dev.: 4,324.8, 7,928 d.f., AIC: 5,836.2.

Table A3. Negative binomial results

Dep Var	Coef	SE	z-Val	p (>|z|)
Intercept	-3.393	0.118	-28.83	< 2E-16***
Free Previews	0.173	0.014	12.72	< 2E-16***
Subscribed Channels	0.029	0.008	3.47	5.25E-4***
AddOnChannels	0.084	0.015	5.40	6.78E-8***

Notes. Signif. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Null dev., 2,832.8 , 7,931 d.f.; res. dev: 2,580.3 on 7,928 d.f.; AIC: 5,484.6.

Table A4. Zero-inflated negative binomial results

Count Model (Negative Binomial with Log Link)				
Dep Var	**Coef**	**SE**	**z-Val**	**p (>|z|)**
Intercept	-2.277	0.298	-7.64	2.22E-14***
FreePreviews	0.194	0.021	9.01	< 2E-16***
Subscribed Channels	0.011	0.012	0.89	0.374
AddOnChannels	0.018	0.022	0.85	0.398
Ln (θ)	-0.350	0.260	-1.35	0.178
Zero-Inflated Model (Binomial with Log Link)				
Dep Var	**Coef**	**SE**	**z-Val**	**p (>|z|)**
Intercept	1.192	0.437	2.73	6.351E-3**
FreePreviews	0.034	0.030	1.10	0.269
Subscribed Channels	-0.040	0.024	-1.63	0.102
AddOnChannels	-0.277	0.075	-3.68	2.33E-4***

Notes. Signif. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; $\theta = 0.703$.