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They all seem good, but which one fits me? Reducing fit uncertainty for digital entertainment goods

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

THEY ALL SEEM GOOD, BUT WHICH ONE FITS ME?
REDUCING FIT UNCERTAINTY FOR DIGITAL ENTERTAINMENT GOODS

A. Phuong Hoang

Singapore Management University
Email: aphoang.2013@phdis.smu.edu.sg

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ABSTRACT

Faster Internet connections and advanced streaming technologies have boosted the consumption of digital entertainment content. Nonetheless, many content providers are still struggling to differentiate their services and sell their offerings in the market, due to the large number of options available and customers' uncertainty about the specific attributes of individual information goods. The providers employ different strategies to communicate information on the quality and fit of their products. In this research, I examine the effectiveness of sampling-based seller strategy on the marketing of digital entertainment goods. Using a large dataset on series drama on-demand, I show that content sampling plays a critical role in reducing consumers' uncertainty concerning fit, thus stimulates more demand. For this class of products, preference fit is more important than vertical quality assessment. The availability of such samples changes consumer purchase behavior by affecting the way they search for and learn about the products. Consumers prefer to seek fit information through more direct sources, even when with additional cost. This research suggests that content providers ought to invest more in strategies that communicate preference fit information to consumers.

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EXECUTIVE SUMMARY

Streaming technology has boosted the production and consumption of digital entertainment goods across platforms. Digital content is disaggregated, marketed and sold on a stand-alone basis. Consumers no long have to subscribe to a channel for one show they like, or buy an album for one song. They can cherry-pick content, and obtain it almost immediately. Nevertheless, there is uncertainty associated with the consumption of these goods: imperfect information on product quality and preference fit. Firms employ different strategies to communicate product information to consumers. Sampling-based strategies, such as the metered-model, and time-locked and feature-limited trials, are commonly used across industries.

I am the first to provide empirical support for the impact of the sampling strategies that are used for encouraging the purchase of series dramas on-demand, a unique class of digital entertainment goods. This study is related to three streams of literature: uncertainty about consumption of experience goods, product sampling, and quality versus fit for digital entertainment goods.

The availability of samples lowers the search cost and changes consumer purchase behavior. For digital goods, horizontal fit in the presence of differentiation is more important than vertical quality assessment. Under uncertainty, consumers naturally look for the best means to learn more about the content, and they prefer to sample more to ensure preference fit, even when doing so incurs additional cost. Therefore, a sampling-based strategy is more effective than other approaches. Thus, service providers ought to invest more in marketing strategies that aim to communicate fit. An appropriate amount of sampling content is the amount that sparks a consumer's interest in the program. This research has direct implications for the marketing of experience goods, and touches on the issues of the disaggregation of digital goods, pirated content, customized delivery and digital convergence.

1. INTRODUCTION

Adults in the U.S. spend an average of 5.5 hours watching video each day (*eMarketer* 2015). Major TV studios, such as ABC and CBS, and content distributors like Netflix or Hulu invest heavily on original shows, in spite of a high failure rate. A successful show provides a network with a competitive edge in sustaining its customer base (Nathanson 2013).

Nevertheless, good shows do not guarantee high viewership, due to the high level of uncertainty associated with their consumption. Entertainment products are horizontally differentiated, which makes it difficult for consumers to select the most suitable program. Firms employ various strategies to overcome this challenge. For example, digital content is delivered on an on-demand basis; consumers can easily search for and purchase the programs anytime and anywhere. In other industries, sampling-based strategies are used to communicate product information. Readers of the *New York Times* can read up to ten articles each month – the *metered model* (Halbeer et al. 2014). Software companies provide basic versions free of charge (Niculescu and Wu 2014). Production companies make trailers and sneak peeks of the movies they produce. Amazon's Kindle employs sampling strategies at the product level for each book, as well as at the service level with its 30-day free trial.

This research extends the literature on sampling strategies for digital entertainment goods, by addressing the impact of sampled content on the purchase of *video-on-demand* (VoD). My view is that a preview does not simply signal quality, it reduces consumer uncertainty concerning fit. I address three questions: (1) What is the impact of free previews on household series purchases? (2) To what extent does household willingness-to-pay for paid previews affect their series purchases? (3) What is the importance of sampled content in the marketing of digital information goods?

2. THEORY

2.1. Consumer Uncertainty and Digital Entertainment Goods

The quality of search goods can be evaluated by inspection before purchase, whereas the quality of experience goods can be determined only after use. Digital entertainment goods are considered experienced goods, as the actual evaluation of quality must come from personal experience. To a viewer, a TV program is better if it fits her taste. So the quality of a show relies on the subjective evaluation of a consumer. Digital entertainment goods are also horizontally differentiated; consumers face higher uncertainty concerning fit when they are given a large number of options (Dimoka et al. 2012). Imperfect information and high uncertainty concerning fit are likely to diminish their willingness-to-pay (Clemons and Markopoulus 2013).

2.2. Product Sampling

Sampling strategies for physical goods. A *sample* is a portion of a product that is given to the consumers free of cost so they may try it before making a purchase decision. *Product sampling* is an effective marketing strategy and business tool whose performance is measurable. It often supports higher conversion rates and return-on-investment. This strategy is expensive to implement though, as firms incur the additional cost of producing and distributing samples.

Sampling strategies for experience and digital goods. Experience goods are characterized by large sunk costs for development, and low fixed costs of reproduction and distribution. Technological advances enable firms to produce samples of their content and distribute them to a large audience. In Marketing and Information Systems research, many studies have examined sampling strategies for information and experience goods. Niculescu and Wu (2013) looked at the *economics of free* under perpetual licensing for two software business models: *feature-limited freemiums* and *uniform seeding*. In the newspaper industry, publishers gain from ads when sampling reduces both the prior expectations and demand of consumers (Halbheer et al. 2014).

Advances in streaming technology have made streaming media affordable, thus increasing the demand for content. Nevertheless, firms need to communicate product information and reduce consumer uncertainty regarding their content offerings, especially for product attributes that address different customers' tastes. Markopoulos and Clemons (2013) studied the beer industry; their research has shown that firms with highly differentiated products experience higher revenue growth when consumers are more informed.

2.3. Quality Versus Fit Issues

The consumer-buying process represents different stages that a consumer will go through. It consists of with problem recognition, information search, evaluation of different options, purchase decision, and post-purchase behavior. When consumers are uncertain about the products, they will continue to search for additional information and have to make a trade-off between effort and accuracy (Mehta et al 2003).

For digital entertainment goods such as a movie, consumers often rely on outside sources of information, including online reviews or word-of-mouth. Social learning and peer effects could have positive impacts on the consumption of movies (Morretti 2011). Consumers will prefer to try out the products directly rather than listening to others' comments (Mehta et al. 2003). For instance, a viewer tends to watch trailers and sneak peeks of the particular movie before buying the movie ticket. Nevertheless, consumers often "choose options that are satisfactory, but would be suboptimal if decision costs were zero" (Haubl and Trifts 2000, p.8).

Quality, by no means, implies fit though. A successful box-office list movie is not necessarily suitable for every audience. Communicating fit is more complicated, and so the implementation of sampling strategies is not that straightforward. Firms need to take into account that individuals value the same product differently. If sampling only signaled quality, or *vertical differentiation*, personal experience with a product would not be necessary. Dey et al. (2013) showed that the *rate of learning* determines the effectiveness of trials for software products. It may take longer for some consumers to evaluate fit, yet offering lengthy samples is not always the best option for content providers (Heiman et al. 2001). Free content may interfere and substitute for the consumption of other programming that generates revenue directly.

3. SELLER SAMPLING-BASED STRATEGY FOR EXPERIENCE GOODS

3.1. Episode Previews for Series Dramas On-Demand

This research was made possible through a partnership with a large digital entertainment firm. Its typical contract term for TV services is three months minimum or longer. There are varied kinds of content from a number of *groups*, such as news, entertainment, sport and educational shows. Customers can specify the groups of content and specific channels to be included in their subscription package.

The service provider also delivers all types of programming on an on-demand basis. On-demand services can be expensive, and it is charged on top of a household’s current TV subscription fee. For each drama purchase, a household can access the content over a fixed period of time – depending on the number of episodes in a drama. Since many series drama are available, it is difficult for consumers to evaluate which suits them best. So service providers offer consumers first episodes of all series dramas for free so the consumer can preview them before making a purchase. I next develop hypotheses on content sampling and purchases of these series.

3.2. Sampling and Purchases

As mentioned earlier, consumers will seek for product information before making purchase decisions. When service providers offer free preview episodes, this will reduce the consumer's search cost for entertainment products. Watching a drama directly via sample episode also reduces a consumer's uncertainty concerning *preference fit* (Markopoulos and Clemons 2013). A consumer can evaluate the quality of the content and whether it fits her preference. The more she samples, the more she is likely to find multiple shows that meet her preference, so that she will purchase more than one series. Free previews, more generally, also encourage consumers to diversify their choices. For instance, a household that normally watches crime-related dramas may preview a romantic drama and find it interesting. And so consumers will be more likely to purchase multiple series across different genres as well.

There are some drawbacks related to *free content* though. Free content may compete with other programs and eventually decreases consumer willingness-to-pay. Consumers may sample many series dramas with no intention to purchase any of them. This scenario is not likely for the majority of consumers in my setting for several reasons, though. First, the viewing experience for a series is not complete without seeing all of its episodes. Indeed, many viewers binge-watch these series: they cannot stop at a few episodes. As a consumer learns more about the plot, she feels the urge to view the rest of the content. Moreover, even households with basic subscription packages have many channels to choose from. So they are unlikely to sample a series if they have no prior interest. So I propose that samples are likely to have a positive impact on a consumer's purchases of VoD drama series:

- **Hypothesis 1 (Household's Free Previews and Series Purchased).** *A household's consumption of free episode previews increases the number of series that it purchases.*

Information search can be costly and time-consuming. Though consumers can learn about the programming through various means, they are likely to update their evaluations of different series and purchase those that satisfy them based on their experiences with free previews. In this case, one episode may not be sufficient for consumers to evaluate fit. After all, it's rarely the pilot that gets consumers hooked on a series.

In our research context, after consumers watch the first episode, they can purchase subsequent episodes separately or purchase the whole series at a discount. The price of a series is fixed, regardless of how many episodes a consumer has already purchased. Purchasing the series after sampling is typically the best option, if the content fits her taste. When consumers are still uncertain about the match of their interests with the content of the series, they will actively seek additional information. They can look for information from secondary sources, or spend $1 or $2 to watch more. As long as a consumer has not purchased the series, a purchased episode is a *paid preview*. I argue that consumers may prefer to buy *paid previews* too; it is an effective way to reduce uncertainty concerning fit. As a household consumer spends more time sampling, she will be more able to evaluate if the content suits her:

- **Hypothesis 2 (Household's Paid Previews and Series Purchased).** *A household's consumption of paid episode previews increases the number of series that it purchases.*

With Hypothesis 2, I propose that consumers ought to be willing to pay more for additional preview, rather than seeking secondary sources of product information.

The consumption of digital entertainment products tends to be influenced by outside information too. Popular series may have received attention from viewers, so these series may be sampled and purchased more. If so, the effectiveness of free previews on a subset of popular series may be over-estimated. Nevertheless, I argue that free previews still play a dominant role in supporting more series purchases. Subjective evaluations of consumers are critical for digital entertainment products. Based on their own sampling experience, consumers will purchase the series that fit their preferences, rather than those that perceived as good quality. Series reviews reduce fit uncertainty, whereas outside information reduces quality uncertainty. So I propose a positive relationship for a drama's samples and purchases, and popularity will play little or no role.

- **Hypothesis 3 (Content Sampling and Series Purchases).** *Content sampling is positively correlated with the purchases of series dramas.*

4. DESCRIPTION OF THE DATASET

Our data were collected through smartcards used in digital set-top boxes for digital cable TV. They store TV subscriber's information and capture all viewing at the household level. For the one-month study period in October 30, 2011, I observed 17+ million *viewing sessions*. There were no holidays during this period that might have influenced households' viewing activities.

A *viewing session* for a TV program occurs when a household starts watching, and ends when the household switches to another channel or turns off the TV. The sessions that involved series drama are classified into three categories: *free episode preview sessions* for first episodes; *paid episode preview sessions* for subsequently purchased episodes; and *paid series sessions* after a series was purchased. I was able to gather all viewing records for 14,470 households, each of which sampled two series on average. I was not able to link all households' subscription information to their respective viewing activities though. Thus, my estimation sample included 19,049 viewing records from 6,338 households, a smaller subset of the data. (Table 1)

Table 1. Background on the Sub-Sample of Data

	Descriptive Statistics					Correlation matrix				
Variable	Mean	SE	Min	Med	Max	1	2	3	4	5
1. *SeriesPurchases*	0.094	0.392	0	0	7	1.00				
2. *PaidPreviews*	0.832	3.414	0	0	67	0.19	1.00			
3. *FreePreviews*	2.078	2.231	0	2	29	0.15	0.05	1.00		
4. *SubscribedGroups*	3.698	1.080	0	3	14	0.08	0.05	-0.03	1.00	
5. *SubscribedChannels*	2.694	2.573	0	2	25	0.10	0.09	-0.03	0.51	1.00

During the study period, the digital entertainment service provider offered 78 on-demand series. Those were a mix of Chinese, Hong Kong, Indian and Indonesian titles. I identified 27 Television Broadcasts Ltd. (TVB) dramas, which were aired during the three-year period, 2009-2011, in Hong Kong. I also obtained additional information regarding those series, such as their viewership ratings and awards they won in Hong Kong.

The ratings and award statistics of these dramas in the Hong Kong market are reasonable indicators of quality and their likelihood of success in other markets. Popular series in Hong Kong are likely to have a spillover effect in the research sponsor's market, due to cultural proximity. These proxies are imperfect, but useful to observe the impact of outside sources of information.

5. EMPIRICAL MODELING APPROACH

I modeled the relationship between *SeriesPurchases* and other related variables as: *SeriesPurchases* = *f* (*FreePreviews, PaidPreviews*; *Controls*). *SeriesPurchases* represents the number of purchases of a series. It is either 0 or a positive truncated number (a count: 1, 2, 3, 4, 5, 6 or 7 maximum). Table 2 presents my two main empirical models and variables.

Table 2. Empirical Models and Variables

VARIABLE NAMES	DEFINITION
HOUSEHOLD LEVEL	
$SeriesPurchases_i = \beta_0 + \beta_1\ FreePreviews_i + \beta_2\ PaidPreviews_i + \beta_3\ SubscribedGroups_i + \beta_4\ SubscribedChannels_i + \varepsilon_i$	
$SeriesPurchases_i$	Number of VoD dramas a household purchased during the period
$FreePreviews_i$	Number of dramas a household sampled during the period
$PaidPreviews_i$	Number of episodes a household purchased during the period
$SubscribedGroups_i$	Control for household's subscription
$SubscribedChannels_i$	Control for household's subscription
SERIES LEVEL	
$SeriesPurchases_j = \beta_0 + \beta_1\ FreePreviews_j + \beta_2\ PaidPreviews_j + \beta_3 AverageRating_j + \beta_4 Awards_j + \xi_j$	
$SeriesPurchases_j$	Number of purchases for a particular drama
$FreePreviews_j$	Number of times a particular drama is sampled (first episode)
$PaidPreviews_j$	Number of episode purchases for a particular drama
$AverageRating_j$	Average ratings of the series in Hong Kong market; proxy for quality information
$Awards_j$	Number of awards the series have won in Hong Kong; proxy for quality information
Notes: The subscript *i* denotes the individual household level; *j* denotes the series level.	

Due to the characteristics of the dataset, I am interested in various count data models. *Count data models* restrict the dependent variable to non-negative integer values. It also considers the relationship between the mean and variance of the distribution that is used to characterize the dependent variable (Cameron and Trivedi 1998).

Poisson regression model is the most popular of the discrete regression models for count data, the events are estimated as independent of one another. It has the following form:

$$y_i \sim Poisson\ (\theta_i) \text{ and all } y_i > 0$$
$$\theta_i = \exp(\textstyle\sum_i^n \beta_i\, x_i) \text{ and all } \theta_i > 0$$
$$y_i \sim Poisson\ (\exp(\beta_0 + \beta_1 X_1 + \ \beta_2 X_2 + \cdots + \ \beta_n X_n))$$

Although the Poisson distribution does not impose any restrictions on the variables, it assumes that the underlying distribution of the dependent variable must have equal means and variances. Our dataset has some characteristics that are inconsistent with this model. At the household level, I observed a sparse dependent variable matrix, which is common in marketing research settings. The mean of *SeriesPurchase* is 0.094, so the majority of the households did not make a purchase, which results in a larger proportion than what one would see for a normal distribution. And at the series level, some are purchased more than the others, due to product heterogeneity.

When the conditional variance of the dependent variable exceeds the conditional mean, this is known as *over-dispersion.* We can calculate the *data-dispersion ratio*; it is more than 1 if there is over-dispersion, or less than 1 if there is under-dispersion. In both cases, the standard errors of the parameter estimates will also be underestimated (Hilbe 2011). *Negative binomial regression* handles the issue of data dispersion with an extra parameter, α, which models the degree of over-dispersion. As a result, the confidence intervals for the negative binomial model are also narrower than those of the Poisson regression model.

Like any time-consuming activity, the consumption of digital entertainment products is subject to several constraints. A household's no-purchase decision may be due to different reasons. For instance, a household may not have money for on-demand content, or it may not have enough time to watch the entire series. In either case, it will not purchase the series. Without these constraints, a household's decision-making process still will be a function of perceived quality and fit. This is the *count process model*, where the *SeriesPurchases* count is influenced by *FreePreviews*. The expected count for different values of k is a combination of the two processes:

$$E\ (Purchases = k) = Probability\ (With\ constraints) \cdot 0$$
$$+\ Probability\ (Without\ constraints) \cdot E(y = k\ |Without\ constraints)$$

To handle this, I chose the *zero-inflated negative binomial regression* model, which has two parts: a *logit model* and a *negative binomial count data model*. The logit part models the probability of excess 0s independently; the probability of *SeriesPurchases* = 0, due to households with insufficient budget or time. The logit and the count part do not need to use the same predictors, and the estimated parameters of the variables do not need to be the same. The probability density function is as follows:

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

$E(y) = \mu_i (1 - \phi)$; $\mathrm{Var}(Y_i) = \mu_i (1 - \phi)\ (1 + k\mu_i + \phi\mu_i)$; μ_i and ϕ depend on the covariates

ϕ is the density function governing the binary process such that $0 \leq \phi < 1$ and the dispersion parameter $k \geq 0$ is a scalar (Lawal 2012). When ϕ or k is greater than 0, there is *over-dispersion*. When $\phi = 0$, the equation reduces to a negative binomial model, and for $k = 0$, it becomes a zero-inflated Poisson model.

6. RESULTS

In this section, I first present the estimation results at the household level, using different count data methods. I then present the results of the analysis at the series level.

6.1. Household Level

The Poisson and negative binomial models' results are reported in Table 3. It provides support for the relationship between previews and series purchases. Table 4 presents the results from the latter model, which accounts for excess no-purchase decisions from different processes.

Table 3. Poisson and Negative Binomial Model Results: Household Level

VARIABLES	POISSON				NEGATIVE BINOMIAL			
	COEF.	SE	z-VAL.	p (>|z|)	COEF.	SE	z-VAL.	p (>|z|)
Intercept	-3.464^{***}	0.139	-24.969	< 0.001	-3.780^{***}	0.180	-21.006	< 0.001
FreePreviews	0.127^{***}	0.010	13.327	< 0.001	0.170^{***}	0.157	10.821	< 0.001
PaidPreviews	0.054^{***}	0.004	13.015	< 0.001	0.106^{***}	0.008	12.476	< 0.001
SubscribedGroups	0.124^{***}	0.039	3.155	0.002	0.136^{**}	0.050	2.731	0.006
SubscribedChannels	0.065^{***}	0.015	4.305	< 0.001	0.084^{***}	0.020	4.237	< 0.001

Notes. Model: Poisson: 6,338 observations. Null deviance: 3,286.8; 6,337 degrees of freedom. Residual deviance: 2,959.6; 6,333 degrees of freedom. AIC: 3,952.9. Model: Negative binomial: 6,338 observations. Null deviance 2,012.8; 6,337 degrees of freedom. Residual deviance: 1,741.0; 6,333 degrees of freedom. AIC: 3,683.7. θ=0.274; degree of dispersion: $\alpha = 1/\theta = 3.649$.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The coefficients for *FreePreviews* and *PaidPreviews* for the Poisson model and the negative binomial model are positive and significant, which provide supports the Household's Free Previews and Series Purchased Hypothesis (H1) and the Household's Paid Previews and Series Purchased Hypothesis (H2). I checked for the Poisson over-dispersion ratio, which turns out to be 1.30. This suggests over-dispersion estimation bias. Note that the negative binomial model coefficients are slightly larger than those of the Poisson model.

The negative binomial model is a better fit for the dataset, so I report its estimates as the main results. If a household were to watch one more free episode preview, its corresponding *incidence rate ratio* will be expected to increase by a factor of 1.185. So households with an additional *FreePreview* will purchase dramas 19% more of the time. Likewise, an additional unit of *PaidPreviews* is associated with 11% more *SeriesPurchases*. I controlled for households' subscription, including *SubscribedGroups* and *SubscribedChannels.*

Table 4. Zero-Inflated Negative Binomial Model Results: Household Level

VARIABLES	ZERO-INFLATED NEGATIVE BINOMIAL							
	COEF.	SE	z-VAL.	p (>|z|)	COEF.	SE	z-VAL.	p (>|z|)
	Count model				*Logit model*			
Intercept	-1.949***	0.253	-7.702	< 0.001	2.121	0.435	4.873	< 0.001
FreePreviews	0.189***	0.021	9.205	< 0.001	0.040	0.029	1.362	0.173
PaidPreviews	0.010	0.009	1.105	0.259	-1.904***	0.383	-4.974	< 0.001
SubscribedGroups	0.033	0.064	0.522	0.602	-0.177	0.118	-1.497	0.134
SubscribedChannels	0.027	0.025	1.072	0.284	-0.094*	0.051	-1847	0.065
Ln (θ)	0.320	0.253	1.263	0.207				
Notes. 6,338 observations. AIC: 3,520.1. θ = 1.377. Significance levels as above.								

In the count part of the zero-inflated negative binomial model, the coefficient of *FreePreviews* is positive and significant. For each additional free preview, the expected change in ln(*SeriesPurchases*) is 0.189. That is, households with an additional *FreePreview* will purchase dramas 21% more of the time; the impact of *FreePreviews* is stronger compared to the results from previous models. The logit part models the excess no-purchase or 0s independently. The log odds of the excess 0s decreases by 1.904 and 0.094 for each paid preview and each channel that a household purchased. Intuitively, the more channels the household has subscribed to, the less likely that the 0s are due to time and budget constraints. The zero-inflated negative binomial model fits the data better than the standard negative binomial regression.

6.2. Series Drama Level

To test for the effect of previews on the sales for each series drama and eliminate potential bias, I looked at series dramas that were similar in terms of their popularity. I ended up with only a few data points left for analysis. Nevertheless, I was interested to see the relative impacts of previews versus the impact of outside quality information on the sales of series dramas. So, I obtained additional information for each series. In this model, I assessed the effect of *FreePreviews* and *PaidPreviews* versus *AverageRating* and *Awards* on *SeriesPurchases*. On one side, there is sampling content impact that reduces uncertainty concerning fit; the other side represents information that signals quality and reduces uncertainty regarding the quality of the series. Table 5 reports my empirical results.

Table 5. Poisson and Negative Binomial Model Results: Series Level

VARIABLES	POISSON				NEGATIVE BINOMIAL			
	COEF.	SE	z-VAL.	p (>|z|)	COEF.	SE	z-VAL.	p (>|z|)
Intercept	1.194*	0.624	1.914	0.056	-0.798	2.030	-0.393	0.694
FreePreviews	0.001***	0.000	6.079	< 0.001	0.001*	0.000	1.881	0.060
PaidPreviews	0.001***	0.000	8.103	< 0.001	0.002***	0.001	2.687	0.007
AverageRating	0.046**	0.022	2.150	0.032	0.108	0.070	1.542	0.123
Awards	-0.039	0.034	-1.148	0.251	-0.072	0.113	-0.634	0.526

Notes. Model: Poisson; 27 observations. Null deviance 1,177.2; 26 degrees of freedom. Residual deviance 268.2; 22 degrees of freedom. AIC: 403.0. Model: Negative binomial; 27 observations. Null deviance 91.0; 26 degrees of freedom. Residual deviance: 29.4; 22 degrees of freedom. AIC: 224.2. $\theta = 2.526$; degree of dispersion: $\alpha = 1/\theta = 0.396$. Significance levels as above.

In both models, the coefficients for *FreePreviews* and *PaidPreviews* are positive and significant, supporting the Content Sampling and Series Purchases Hypothesis (H3). The coefficients for *AverageRating* and *Awards* in the negative binomial model are not significant. This provides evidence that content sampling is more effective in stimulating more purchases, by specifically reducing uncertainty regarding preference fit for experience goods.

7. CONCLUSION

Previews play an important role in engaging the consumers, stimulating more purchases. The market for series on-demand is unique for gauging the impact of content previews, in which series dramas are offered as an on-demand service to consumers. Previews had a positive impact on a number of drama purchases; an additional free episode preview was associated with a 21% increase and an additional paid episode preview led to an 11% increase in series purchases.

Households were willing to pay more for paid previews to ensure that the series fit their preference, since one episode is rarely sufficient to signal fit and spark households' interest. After controlling for a household's subscription information, I found the effects of previews on purchases are still significant.

There are some limitations of this research though. First, the dataset prevented me from exploring the impact of free previews on sales for a particular drama over a longer time horizon, which would have been revealing in other ways. Second, all of the viewing timestamps were recorded in time blocks. I could not extract the viewing durations; thus it is hard to make conclusions on absolute viewing time for previews relative to household series purchase behavior.

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