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Willingness to Pay for Digital Contents in Japan

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Abstract

We estimate a mixed logit demand model for the Japanese digital content market and measure willingness to pay for service attributes. We find that the willingness to pay for an extra unit of service quality ranges from 62 Yen to 83 Yen per month. Meanwhile, the switching cost, a measure of disutility from switching to other service providers is estimated as 340 Yen ($3) per month, which is approximately the same as the current monthly subscription fee.

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I. Introduction

In this paper we estimate a mixed logit demand for the digital content in the Japanese PC and mobile markets and measure consumer's willingness to pay for service attributes. We first estimate a demand function of digital contents using a hierarchical Bayesian model (Allenby, 1997, Train 2001) and analyze how the service attributes affect the consumers' utility. We then use the estimated parameters in the demand function to measure consumers' willingness to pay for each service attribute. In particular we are interested in the measurement of willingness to pay for switching to other service providers. Usually, switching behavior is influenced by switching cost, which is defined as any perceived disutility a consumer would experience from switching service providers (e.g., Klemperer, 1987).

We find that the service attributes have significant effects on the consumers' utility and their preference for the service attributes is distributed with a large variance across the consumers. We also find that willingness to pay for more robust content was 83 Yen per month and that for content update frequency was 62 Yen per month. Meanwhile, the overall consumer switching cost was 340 Yen (about US$3) per month, which is approximately the same as the current content subscription fee of 300 yen per month. We also find that the switching is highly correlated with service quality, in particular, service robustness, provided by other service providers.

II. Market and Data

We collected data using a choice-based conjoint (CBC) survey to examine consumers' preferences regarding digital content and their loyalty to the providers of such content. In the analysis, each surveyed consumer was presented with several hypothetical offers by content service providers and was asked to identify which offer the consumer would choose. Additionally, for each set of hypothetical offers, respondents were also given the choice to reject all offers provided.

For this research, respondents were recruited from mobile and PC content subscribers. The paper specifically focused on two of Japan's most powerful consumer brands offering content via PC and mobile channels, Disney and Yahoo!. According to the 2005 Nikkei Brand Japan survey, these two brands were the two highest-ranked Internet and service companies in Japan. In this study, in total n=825 Disney or Yahoo! respondents randomly recruited from Macromill Inc.'s 1.8 million member subscriber panel. On this panel, 45% (n=372) of respondents were female and the other 55% were male. The average age of respondents was 33 years with a standard deviation of 8.9 years. In total, all 47 prefectures and wards across Japan were represented. The survey was filed in March 2006, using an Internet-based survey interface.

Respondents answered demographic questions about themselves along with a total of 15 conjoint analysis choice experiments. In each experiment, respondents were asked to select from five conjoint cards that contain different brands with different attributes. The number of choice experiments was designed to provide a wide variation in choices for each attribute. Because Yahoo! And Disney competitors are distinctly different, separate competitors were chosen for Disney and Yahoo! Subscribers in the conjoint experiments. For Disney subscribers, competing brands included in the conjoint experiments were Bandai Networks, Studio Ghibli, Nana, and Doraemon. For Yahoo! Subscribers, competing brands included in the conjoint experiments consisted of the top five competitive Japanese web portals to Yahoo!Japan in terms of overall traffic, including Google, Rakuten, Infoseek, MSN and goo. All these portal sites were available both via the PC and the mobile phone.

The price attribute represented the monthly subscription fee for digital content, and had six levels which increased in 100 Yen/month increments, ranging from level 1, "free" (or 0 Yen/month) to level 6 "500 Yen/month". The content robustness attribute represented the richness of the content provided, and had five levels, ranging from level 1"much less robust content than my current content provider." to level 5 "much more robust content than my current content provider" Finally, the content update attribute represented the frequency at which new content is added to an existing digital content service. This attribute consisted of six levels ranging from level 1, "content is updated less than once a month" to level 6 "content is updated every day."

III. The Model

We estimate consumer utility from content use with a mixed logit model, which provides a flexible specification for representing the distribution of preferences in the population and the choices of each customer (Bhat, 1999; Brownstone and Train, 1999; Train, 1998; Lee et.al, 2006).

Consider a choice among alternatives *J=1, 2,…, J* in choice situations *t=1, 2,…, T.* Then the utility that consumer i obtains from choosing choice j in situation t is

$$U_{njt} = \beta_n ' x_{njt} + \varepsilon_{njt} \ (1),$$

where ε_{njt} is the iid extreme value error term and β_n denotes the value that each consumer places on the attributes and is normally distributed with mean *b* and variance *W*, i.e., $\beta_n \sim N(b,W)$. β_n varies randomly over consumers, reflecting the range of consumer preferences regarding service providers' attributes. x_{njt} represents a vector of choice characteristics that include price and the dummy for switching, content robustness, and content update. The switching dummy is equal to 1 if a consumer chooses an alternative to her present service provider and 0 otherwise. We can then rewrite the utility function as follows.

$$U_{njt} = \beta_{n1} Price_{njt} + \beta_{n2} \cdot Switching + \beta_{n2} \cdot ContentRobustness_{njt} + \beta_{n4} \cdot ContentUpdate_{njt} + \varepsilon_{njt}$$

(2)

where β_{nk} is the consumer n's coefficients for attribute *k.* We estimate the mixed logit model using the hierarchical Bayesian method (Allenby 1997, Train 2001, Train et al. 2003).

Suppose that a study has priors on *b* and *W*. The prior on *b* is assumed to be normal with an unboundedly large variance while the prior on *W* is assumed to be inverted Wishart with K degrees of freedom and scale matrix *I*, the K-dimensional identity matrix. Let's denote consumer n's chosen alternative through all time as $y'_n = (y_{n1}, y_{n2}, ..., y_{nT})$. The chosen alternatives across the entire sample are then represented as $Y = (y_1, y_2, ..., y_T)$. Then the conditional on β_n , i.e., the probability of consumer n's observed choices, is

$$L(y_n \mid x_n, \beta) = \prod_t^T \frac{\exp(\beta' x_{ny_{nt}t})}{\sum_j \exp(\beta' x_{njt})} \qquad (3)$$

The unconditional probability is the integral of $L(y_n \mid b, W)$ over all values for β :

$$L(y_n \mid b, W) = \int L(y_n \mid \beta) \phi(\beta \mid b, W) d\beta \qquad (4),$$

where $\phi(\beta \mid b, W)$ is the normal density with mean *b* and variance *W*. $L(y_n \mid b, W)$ is the mixed logit probability. The posterior distribution of *b* and *W* is

$$K(b, W \mid Y) \propto \prod_n L(y_n \mid b, W) k(b, W) \qquad (5),$$

where $k(b, W)$ is the prior on *b* and *W*, i.e., normal for *b* times inverted Wishart of *W*. Our goal is to obtain information on the population distribution of preferences associated with each attribute of service providers. For this purpose, we take draws from the posterior distribution to get information about the posterior. We use Gibbs sampling to take draws where draws are taken sequentially from the conditional posterior of each parameter given the previous draw of the other parameters. The sequential of draws from the conditional posteriors converges to draws from the joint posterior.

We assume that the parameters in the utility function are distributed normally. In many applications, however, such an assumption may be inappropriate. A normal distribution for a price coefficient implies that some consumers prefer higher prices. Willingness to pay for an attribute can be unboundedly high for consumers whose price coefficients are near zero, because willingness to pay is the coefficient of the attribute divided by the price coefficient (Train et. al, 2003). In this paper, we therefore transform the price coefficient to lognormal distribution such that the price coefficients for all consumers have the same sign. In estimation, the negative of price data is entered such that the coefficient on price is positive for all consumers. We can therefore interpret the positive coefficient as the preference for price reduction.

Table1. Estimation of Population Parameters

	Mean of β	Variance of β
Price	-0.3764 (0.0472)	1.0568 (0.0987)
Switching	-1.2590 (0.0818)	2.3754 (0.2340)
Content Robustness	0.3064 (0.0217)	0.1508 (0.0155)
Content Update	0.2276 (0.0184)	0.0997 (0.0107)
Log likelihood	-7122.63	

Note: The numbers in parentheses are standard errors

IV. Results

Table 1 represents the estimated parameters in the mixed logit model. These are the means of the 1000 draws of b and of the diagonal elements of W. From the classical perspective, these are the estimated population means and variance of β_n . All the estimates are significant. At the mean, switching has a negative effect on utility. Content robustness and content updates have positive effects on utility. In particular, the highly significant variances indicate that parameters do indeed vary in the population. This also suggests that the mixed logit model is more appropriate than a logit model that imposes the same coefficients for attributes across consumers. The mixed logit technique allows each coefficient to have a mean and variance in the population, while standard logit contains fixed coefficients, which is equivalent to a mixed logit with zero variances.

Table 2. Mean and Variance of Coefficients with Transformation of normal

	Mean	Variance
Price	1.1522	2.6851
Switching	-1.2671	2.4493
Content Robustness	0.2990	0.1616
Content Update	0.2284	0.0973

Table 2 presents the mean and variance of coefficients. Two thousands draws of β_n were taken from a normal distribution with mean equal to the estimated value of b and variance equal to W. Each draw of β_n was then transformed to obtain a draw of coefficients as shown in Table 2. Table 3 shows the distribution of population for each coefficient. For 78.6% of the population, switching to other service providers produces a negative effect on utility. A similar proportion of the population, 78.3%, prefers content robustness while the rest of the population dislikes it. Content update produces positive utility for 76.5 percent of population, which means that it produces negative utility for the remaining 23.5 percent.

Table 3. Share of population for coefficients with
Transformation of normal .

Coefficient	Shares strictly below zero and at zero(%)
Price	0.0
Switching	78.6
Content Robustness	21.7
Content Update	23.5

Table 4 presents correlations among coefficients. It indicates that switching is positively correlated with content robustness and content update. This suggests that even though switching to another provider is costly, consumers are willing to switch insofar as other brands provider better content robustness and content update. Switching is positively correlated with reduction in price. If other service providers charge high prices, consumers will not switch. The results also show that switching is correlated more strongly with content robustness than with other attributes.

Table 4 Correlations among coefficients with transformation of normal

	Price	Switching	Content Robustness	Content Update
Price	1.00	0.120	0.108	0.008
Switching		1.00	0.361	0.222
Content Robustness		1	1	0.272
Content Update				1

As Table 2 indicates, 78.6% of the population suffers utility loss from switching to other service providers. Therefore, without compensation, consumers will not switch. How much, then, should they be compensated? Table 5 shows the estimated consumers' willingness to pay for each attribute. The willingness to pay for each attribute is calculated as the marginal utility of each attribute, $\partial U_{njt} / \partial x_{njt}$, divided by the negative of the derivative of utility with respect to price, i.e., the price coefficient. Willingness to pay for switching providers, i.e., the switching cost, is negative 340 Yen (US$3) per month. This amount is approximately the same as the current monthly subscription fee for mobile digital content of 300 yen per month. Meanwhile, for content robustness and content update, consumers are willing to pay 83 Yen and 62 Yen a month more for each unit of increase, respectively.

Table 5 Willingness-to-Pay (Unit: 100 Yen/month/unit)

	Mean	Median	Variance
Switching	-3.40	-3.36	0.26
Content Robustness	0.83	0.82	0.02
Content Update	0.62	0.61	0.01

V. Conclusion.

In this paper we estimate consumers' utility function for the Japanese mobile and PC content market and analyzed how service attributes affected the consumers' utilities. We find that the consumers are willing to pay a large monthly fee, which is approximately the same as the current monthly subscription fee not to switch to other service providers and that consumers' switching is largely affected by the service attributes provided by competitors. The results imply that high quality service makes it possible for service providers to charge high monthly fees and to prevent consumer switching.

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