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Discrete Choice Model Analysis of Mobile Telephone Service Demand in Japan

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DISCRETE CHOICE MODEL ANALYSIS OF MOBILE TELEPHONE SERVICE DEMAND IN JAPAN

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Abstract:

This paper analyzes the demand for mobile telephones including second generation (2G) and third generation (3G) by using a discrete choice model called a mixed logit model. First, we examine the substitution patterns of the demand for mobile telephones and show that demand substitutability among alternatives is stronger within the provider nest category than within the standard nest category in mobile telephone services. The closest substitute for NTT's 3G service is NTT's 2G service, rather than KDDI's 3G service, for example. Second, we investigate the elasticities of demand for various functions including e-mail, Web browsing, and moving picture delivery. Consequently, we cannot observe marked differences between 2G and 3G services based on these calculated elasticities, indicating that it takes time for 3G subscribers to gain proficiency with such new services.

JEL classifications: L52; L86; L96

Keywords: discrete choice model, mixed logit model, mobile telephone, cellular phone, IMT 2000

I. INTRODUCTION

As of September 2004, the number of Japanese mobile telephone subscribers reached 84 million, easily surpassing the 60 million fixed telephone subscribers. Mobile Internet service started in February 1999, and third generation (3G) mobile telephone services appeared on the market in October 2001, both of which were the first such introductions in the world. Furthermore, mobile telephone functions have remarkably diversified from simple voice and data transmissions to built-in camera phones, financial transactions, and TV and radio reception. The purpose of this paper is to investigate this rapidly evolving demand for mobile telephone services including 3G services by using a discrete choice model called a mixed logit model.

First, a brief review of the related literature shows that few papers have studied demand for mobile telephone services, as previously pointed out by Taylor (2002 p.130). Research on demand for 3G services is even less common. An exception is Kim (2005), who investigated consumer stated preferences for 3G services (IMT 2000) in Korea by using conjoint analysis. For our purposes, significant analysis of demand for mobile telephone services can be seen in the following cross-comparative and country studies. For cross-country research, Ahn and Lee (1999) compared the subscriber rates of mobile telephone services in developed countries and found that income is a more important attribute than charges. Wallsten (2001) explored the effects of privatization, competition, and regulation on mobile operator performance in 30 African and Latin American countries, and Madden et al. (2004) estimated elasticities of demand for mobile telephone service with respect to price and income, based on panel data from 56 countries. Liikanen et al. (2004) analyzed the role of generational effects in diffusion, interestingly finding positive within-generation network effects.

For country case studies, Tishler et al. (2001) and Kim and Kwon (2003) analyzed mobile telephone demand by using the multinomial logit model: the former offered projections for the Israeli mobile telephone market up to 2008, while the latter discussed the advantages of network size in acquiring new subscribers in the Korean mobile telephone market. On the other hand, Ahn (2001) estimated the access demand for mobile telephone service in Korea and found that age, gender, and education are important determinants. Finally, Iimi (2005) analyzed the Japanese mobile telephone service industry, concluding that the market is highly product-differentiated and no longer displays conventional network externalities.

This paper analyzes the access demand for Japanese mobile telephone services by using a discrete choice model. It makes two contributions. This paper analyzes consumers' revealed preferences regarding mobile telephone subscriptions with a special emphasis on the differences between 2G and 3G services, and thus far, is considered one of the first few studies that explicitly deal with 3G services. To analyze decision-making structures in Japan's mobile telephone market, we need to relax the independence from irrelevant alternatives (IIA) properties imposed on conditional logit (CL) models. In this paper, we adopt a mixed logit (ML) model that can flexibly express an analog to an overlapping nested structure made possible only by recently developed econometric innovations.

The two main conclusions obtained in this paper are summarized as follows. First, we investigate substitution patterns in mobile telephone services and conclude that demand substitutability among alternatives is stronger within the provider nest category than within the standard nest category. The 1% increase in the basic monthly charge of NTT's 3G service (called FOMA) decreases its choice probability by 0.8%. At the same time, this increases the probability of choosing NTT's 2G service (called MOVA) by 0.5% but the probability of choosing KDDI's 3G service (called CDMA 2000) only by 0.1%. We thus see that the closest substitute for NTT's 3G service is NTT's 2G service, rather than KDDI's 3G service. The same thing can be said of NTT's 2G service. These conclusions demonstrate that many mobile telephone subscribers apparently feel *locked in* their current providers because the costs of switching providers are quite high, especially considering e-mail addresses and various discount packages (e.g. family membership and long-term contracts, etc.).

Next, we analyze the elasticities of demand for various functions. Looking at explanatory variables whose t-values are statistically significant, including e-mail, Web browsing, moving picture delivery, we cannot confirm that the elasticities of demand are clearly different between 2G and 3G services. A possible reason is that the transition from 2G to 3G services is ongoing, and even 3G subscribers fail to display outstanding utilization that differs from existing 2G services. However, based on the data available under the present circumstances described above, it would be hasty to conclude that the newly-introduced 3G service package is less attractive than that of its precursor 2G because function utilization rates vary qualitatively and quantitatively over time.

This paper is organized as follows. Section II introduces sample surveys and the data. Section III explains the estimation model and examines the advantages of the ML model. Section IV analyzes the estimation results, looking closely into the elasticities of demand with respect to price and functions. Finally, Section V provides concluding remarks.

II. SURVEY METHOD AND DATA

This section introduces the survey and data used in this paper. We carried out sample surveys on individual usage of mobile telephones and PHS in September 2004 jointly with the Japanese Ministry of Internal Affairs and Communication (MIC). The survey was conducted on 1000 monitors (aged 20 years old and above) registered with eleven local offices of MIC. The number of respondents was 939. Among them, 764 people (81.4%) subscribe to a mobile telephone or PHS. Excluding omissions, we finally obtained 687 effective respondents whose breakdown is given in Table I according to technical standards (i.e., 2G, 3G, and PHS) and providers (i.e., NTT DoCoMo, KDDI (au and Tu-ka), and Vodafone).

<Table I: BASIC STATISTICS OF DATA>

The choice ratios are broken down into 3G (37.5%), 2G (57.4%), and PHS (5.2%) according to technical standards. Compared to actual market shares, the 3G choice ratios are higher in our survey, indicating that the monitors registered with the survey are more interested in telecommunications services than the average Japanese person[1]. Also, by provider the choice ratios are NTT (50.2%), KDDI (29.1%), and Vodafone (19.8%). Compared to actual market shares, NTT's choice ratio is lower in our survey, which is in part based on the fact that the 3G choice ratio is higher in our sample survey and that NTT's share is not so high in the 3G market.

Let us now examine the details. *Monthly Expenditure* includes basic monthly charges, additional function charges, call charges, and packet-switched data

[1] According to the MIC, actual market shares for the technical standards were 3G (27.1%), 2G (67.6%), and PHS (5.3%); while provider market shares are NTT (56.1%), KDDI (26.0%), and Vodafone (17.9%) as of September 2004.

transmission charges[2]. 3G services are more expensive than 2G and PHS services, and the monthly expenditures of NTT are also more expensive than KDDI and Vodafone. *Call Time* indicates minutes called per week. 3G services accumulate more minutes than 2G and PHS services; likewise, NTT's 3G accumulates more call time than KDDI and Vodafone. *Mail No.* indicates the number of sent/received e-mails per week. Note that 87.7% of mobile telephone subscribers who replied said that they use e-mail services by mobile telephone. There is no big difference between 2G and 3G services while PHS mail number is much smaller, and Vodafone subscribers use e-mail services more frequently than NTT and KDDI subscribers. *Web Browsing* represents the number of users who replied that they frequently use Web browsing services by mobile telephone. 49.3% of mobile telephone subscribers frequently use Web browsing services. 3G service ranks first, followed by 2G service and then PHS service; NTT also leads KDDI and Vodafone in Web browsing. *Picture* represents the number of users who replied that they frequently use still-picture delivery services by mobile telephone. 12.5% of mobile telephone subscribers frequently use still picture delivery services. 3G service ranks first, followed by 2G service and PHS service, and KDDI also slightly leads Vodafone and NTT in picture delivery service. *Movie* represents the number of users who frequently use moving picture delivery services via mobile telephone. This service is basically provided by 3G services, and only 10.9% of 3G subscribers frequently use moving picture delivery services. Only 3.5% of 3G subscribers use TV telephone services. The last two facts demonstrate that 3G high-speed data transmission services have not yet been fully utilized.

III. ECONOMETRIC MODEL

In this paper, we analyze mobile telephone service demand by using a discrete choice model. Conditional logit (CL) models that assume independent and identical distribution (IID) of random terms have been widely used in past studies. However, independence from the irrelevant alternatives (IIA) property derived from the IID assumption of the CL model is too strict to allow for flexible substitution patterns. A

[2] Figures represent amounts subtracted by various discount services and do not include information service charges.

nested logit (NL) model partitions the choice set allowing alternatives to have common unobserved components compared with non-nested alternatives by partially relaxing strong IID assumptions. However, even the NL model is not suited for our analysis because of its arbitrary nature in determining the nested structure. Though the factors of technical standard or provider brand are both important to mobile telephone subscribers, we have no information about which factor predominates in the decision-making of mobile telephone subscribers. In such a case, we need to construct an overlapping nested structure composed of both technical standard and provider brand. Consequently, the most prominent model is a mixed logit (ML) model that accommodates differences in covariance of the random components (or unobserved heterogeneity). ML models are highly flexible to obviate the limitations of the CL model by allowing for random taste variation, unrestricted substitution patterns including overlapping nested structure, and the correlation of random terms over time (see McFadden and Train 2000, Ben-Akiva, Bolduc, and Walker 2001 for details).

III(i) Mixed Logit (ML) Model

Here we explain a ML model assuming that parameter β is distributed with density function $f(\beta)$ (see Train 2003, Louviere et al. 2000). The logit probability of decision maker *n* choosing alternative *i* is expressed as

$$L_{ni}(\beta) = \exp(V_{ni}(\beta)) / \sum_{j=1}^{J} \exp(V_{nj}(\beta)),$$

which is the normal logit form, given parameter β, the observable portion of the utility function V_{ni}, and alternatives $j=1, \ldots, J$. Therefore, the ML choice probability is a weighted average of logit probability $L_{ni}(\beta)$ evaluated at parameter β with density function $f(\beta)$, which can be written as

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta .$$

ML models are also referred to as random parameter models if focusing on the distribution of parameters, or as error component models if focusing on the flexible substitution pattern (cf. Revelt and Train 1998, Brownstone and Train 1999). Following the latter line, the utility function can be written as

$$U_{ni} = \alpha' x_{ni} + \beta' z_{ni} + \varepsilon_{ni},$$

where x_{ni} and z_{ni} respectively denote observable variables, α fixed parameters vector, β random parameter vector, and ε_{ni} independently and identically distributed extreme value (IIDEV) term.

ML models can represent an analog to NL models by specifying a dummy variable z_{ni} for each nest that equals one for each alternative in the nest and zero for alternatives outside the nest. To express the *K* non-overlapping NL model, the error component is set at $\beta_n z_{nj} = \sum_{k=1}^{K} \beta_{nk} d_{jk}$, where $d_{jk} = 1$ if the alternative is in nest *k,* and zero otherwise, and β_{nk} is independently normally distributed as $N(0, \sigma_k)$. Allowing different variance σ_k for the random variables for the different nests is analogous to allowing inclusive value (IV) parameters to differ across the nests in the NL model. We can even express the overlapping NL model with dummy d_{jk} that identifies overlapping sets of alternatives (see Ben-Akiva et al. 2001, Train 2003 for details).

The demand elasticity of the ML model is the percentage change in the ML choice probability for one alternative, given a change in the *k*-th attribute of the same or another alternative. ML elasticity can be expressed as

$$E^{ni}_{x_{knj}} = -\int \beta_k L_{nj}(\beta) [\frac{L_{ni}(\beta)}{P_{ni}}] f(\beta) d\beta,$$

where β_k is the *k*-th coefficient. This elasticity is different for each alternative, and here the constant cross-elasticity property derived from the IIA property does not hold.

Since the ML choice probability is not expressed in closed-form, simulations need to be performed for the ML model estimation. Let θ be a deep parameter of parameter β, in other words, the mean and covariance of the parameter density function $f(\beta \mid \theta)$. ML choice probability is approximated through the simulation method. Concretely, the simulation is carried out as follows (see Train 2003 p.148 for details): first, draw a value of β from $f(\beta \mid \theta)$ for any given value of θ, and repeat this process *R* times (labeled $\beta^r, r = 1...R$); second, calculate the logit formula probability $L_{ni}(\beta)$ with each draw; and third, averaging $L_{ni}(\beta)$, the simulated choice probability is obtained as

$$\hat{P}_{ni} = \frac{1}{R} \sum_{r=1}^{R} L_{ni}(\beta^r).$$

This simulated choice probability $\hat{P}_{ni}$ is an unbiased estimator of P_{ni} whose variance decreases as R increases. The simulated log likelihood (SLL) function is given as

$$SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \ln \hat{P}_{ni} ,$$

where $d_{nj} = 1$ if decision maker n chooses alternative j, and zero otherwise. The maximum simulated likelihood (MSL) estimator is the value of θ that maximizes this SLL function.

In what follows, we adopt the ML model for the estimation, specify dummy variables for 2G and 3G users and for NTT and KDDI users, respectively, in such a way that these dummy variables intersect with random parameters. Accordingly, we can express an analog to the overlapping nested structure of decision making in mobile telephone services. We then use the MSL method for estimation by setting 100 time random draws[3] [4].

III(ii) Variables

Here we explain the explained and explanatory variables in our model. First, the explained variables are the following six alternatives[5]:

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[3] Louviere et al. (2000 p. 201) suggest that 100 replications are normally sufficient for a typical problem involving five alternatives, 1000 observations, and up to 10 attributes (see also Revelt and Train 1998), although the number of random draws is still an issue of controversy.

[4] The adoption of other draw methods including Halton sequence draw is an important problem to be examined in the future (see Halton 1960). Bhat (2001) found that 100 Halton sequence draws are more efficient than 1000 random draws for simulating a ML model. However, an anomaly may arise in this analysis, and therefore the properties of Halton sequence draws in simulation-based estimation needs to be investigated further (see Bhat 2001, Train 2003). As a matter of fact, we could not obtain stable estimation results using Halton sequence draw, whereas the results were quite stable when using random draws. This is why we adopt random draw for our analysis. Determining the suited draw method is still open for future research.

[5] McFadden (1984) claimed that it is difficult to obtain reliable estimations for an alternative that has less than 30 samples. Therefore, we deleted Vodafone's 3G service from the choice set, integrated au's 2G service and Tu-Ka's service into KDDI's 2G service, and considered various PHS services as one brand.

- NTT's 3G
- KDDI's 3G
- NTT's 2G
- KDDI's 2G
- Vodafone's 2G
- PHS

Next, we define the explanatory variables as follows:

- Constant: Dummy variables are specified for 2G, 3G, NTT, and KDDI users. As such, for example, the constant term for NTT's 3G is expressed as the sum of the 3G dummy coefficient and the NTT dummy coefficient.
- Flat Rate: Monthly Expenditures in Table I are composed of monthly flat charges and usage charges that increase with call time. Therefore, monthly expenditure is not a proper explanatory variable because it is endogenously determined by other explanatory variables such as call time: an increase in call time increases monthly expenditures. At this point, we adopt the following strategy to avoid this problem: we first regress Monthly Expenditure on Call Time and other variables including Mail No., Web Browsing, Picture, and Movie, and, second, separate the monthly expenditure into flat rate and usage rate parts. Following Kim (2005), we define flat rate independent of call time as a basic price variable[6] [7]. Table II depicts the separation of monthly expenditure into flat rate and usage charges[8].
- Call Time: call minutes per week.
- Mail No.: number of sent/received e-mails per week.

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[6] Since discrete choice models are normally concerned with the analysis of access demand, the flat rate component is considered a basic price variable where a tariff structure takes the form of a complicated multipart system (see Train 2003, for example).

[7] Strictly speaking, we should have extracted the usage rate charge that depends on data transmission from the flat rate charge. However, we do not exclude data transmission fees from flat rate charges because the flat rate system for data transmission has significantly penetrated Japanese mobile telephone services.

[8] Note that all flat rate and usage charge estimates are statistically significant at the 1% level according to t-values.

- Web: dummy variable for an individual who often uses Web browsing services.
- Picture: dummy variable for an individual who often uses still picture delivery services.
- Movie: dummy variable for an individual who often uses the moving picture delivery service.

<Table II: SEPARATION OF MONTHLY EXPENDITURE INTO FLAT RATE AND USAGE CHARGES>

For parameters, the utilities derived from various functions are likely to differ between the 2G and 3G services because the service quality varies. Therefore, we estimate different parameters for technical standards. Furthermore, such explanatory variables as Call Time, Mail No., Web, Picture, and Movie are so-called *individual characteristics*. Since only the differences of utility parameters between two alternatives matter in the discrete choice model analysis, we actually measure the influences of individual characteristics on the choice probabilities of 2G and 3G alternatives on the basis of the PHS alternative (see Greene 2003 for details). For example, parameter Call Time 3G represents an incremental utility of choosing the 3G alternative compared to the PHS alternative[9].

IV. ESTIMATION RESULTS

This section discusses the estimation results of the ML model. Results are given in Table III[10]. First, we see that Constants (means of 2G and 3G), Flat Rate (2G, 3G), Mail (2G, 3G), Web (2G, 3G), and Movie (2G, 3G) are statistically significant at the 5% level, according to the t-values. Assuming that parameters for 2G, 3G, NTT, and KDDI dummies are normally distributed, correlations between alternatives are allowed here. The values of standard deviations of random parameters are not statistically

[9] Note that for this reason parameters such as Call Time (PHS), Mail No. (PHS), and so on do not appear explicitly in Table III.

[10] Before estimating the ML model, we carried out ordinary CL model estimation and confirmed that the IIA property is rejected at the 1% statistically significant level because the value of Hausman test statistic is 48.24 when we excluded KDDI's 2G alternative.

significant except that NTT is statistically significant at the 10% level[11]. However, the IIA property is completely relaxed in the ML model so that flexible substitution patterns can be expressed. A strong point of the ML model can be seen in that cross elasticities of demand are all different, which will be discussed in the next subsection.

<Table III: ESTIMATION RESULTS>

IV(i) Price Elasticities

We investigate the elasticities of access demand (choice probability) with respect to monthly flat rate price (hereafter price elasticities). There are two kinds of price elasticities. The first is own (or direct) elasticity, which measures the percentage change in the choice probability with respect to a given percentage change in the price of the same alternative. The second is cross elasticity, which measures the percentage change in the choice probability with respect to a given percentage change in the price of another alternative. Calculation results are indicated in Table IV.

<Table IV: PRICE ELASTICITIES>

Looking at the first row, with respect to NTT's 3G price, the own elasticity of NTT's 3G is -0.783, and cross elasticities are 0.067 for KDDI's 3G, 0.471 for NTT's 2G, 0.055 for KDDI's 2G, 0.213 for KDDI's 2G, and 0.203 for PHS. Note that cross elasticities vary across alternatives because the IID assumption is completely relaxed here.

Let us go into the details. A 1% decrease in NTT's 3G flat rate price increases the probability of choosing NTT's 3G by 0.8%. At the same time, this price change decreases the probability of choosing NTT's 2G by 0.5%, while decreasing the probability of KDDI's 3G by only 0.1%. The closest substitute for NTT's 3G is not KDDI's 3G but NTT's 2G. Similarly, the 1% decrease in NTT's 2G flat rate price increases the probability of choosing NTT's 2G by 0.3%. At the same time, this price

[11] Since the IIA property has already been rejected, we should not return to a non-random parameter CL model.

change decreases the probability of choosing NTT's 3G by 0.2%, while hardly affecting the probability of KDDI's 2G and decreasing the probability of choosing Vodafone's 2G by only 0.1%. The closest substitute for NTT's 2G is neither KDDI's 2G nor Vodafone's 2G but NTT's 3G. The same thing applies to KDDI's 3G and 2G. Consequently, the demand substitutability of mobile telephone services works not within technical-standard categories but within the provider-brand categories. A possible reason is that subscribers tend to be locked in to their current providers through switching costs caused by telephone numbers, e-mail addresses, family-member discount services, long-term discount services, and so on[12].

Next, we compare the total price elasticities according to technical standards (namely, 2G and 3G). The total price elasticities of 3G services can be derived in the following way (see Motta 2003, pp.125-126)[13]. Suppose that the prices of NTT's 3G and KDDI's 3G services increase independently and simultaneously by 1%; the probability of choosing NTT's 3G decreases by 0.783% with a 1% increase in NTT's 3G price but increases by 0.032% with a 1% increase in KDDI's 3G price; in sum, the total price elasticity of NTT's 3G is 0.751. In the same way, the total price elasticity of KDDI's 3G is 0.497. Turning to the total price elasticities of 2G services, the values are 0.214 for NTT'S 2G, 0.179 for KDDI's 2G, and 0.179 for Vodafone's 2G. It follows that 3G services are more price-sensitive than 2G services based on total price elasticities. In other words, the probability of choosing 3G services changes more sensitively than 2G services for percent changes in prices.

IV(ii) Other Elasticities

We then refer to other elasticities with respect to various functions including e-mail, Web browsing, and moving picture delivery that are statistically significant variables.

Table V indicates the demand elasticities for the number of e-mails per week. There is only a small difference between NTT's 3G and NTT's 2G and between KDDI's 3G and KDDI's 2G for e-mail own-elasticities. This is probably because 3G services have

[12] Note that MIC has decided to introduce a number portability system into the Japanese mobile telephone market in 2006 to encourage competition.

[13] McFadden (1979) suggests an aggregation rule of elasticities over multiple alternatives and variables.

an advantage over 2G services for simple text message services.

<Table V: E-MAIL ELASTICITIES>

Table VI indicates demand elasticities with respect to the frequent use of Web browsing services. The figures are about 0.5 for 3G services and about 0.4 for 2G services; the Web-browsing elasticities are a little larger for 3G services than for 2G services, reflecting that Web browsing requires larger volume data transmission, and 3G service has an advantage over 2G service in this respect, although the difference of elasticities is still small.

<Table VI: WEB BROWSING ELASTICITIES>

Lastly, Table VII indicates the demand elasticities of the frequent use of moving picture delivery services. The figures of the elasticities are less than 0.1 for 3G services. Although moving picture delivery service is statistically significant, its positive impact on the probability of choosing 3G services is quite small. Although a moving picture delivery service that requires high-speed, large-volume data transmission is thought to be a "killer application" for further diffusion of 3G services, it has not yet been fully utilized by 3G subscribers.

<Table VII: MOVING PICTURE ELASTICITIES>

In conclusion, after examining demand elasticities for various functions including e-mail, Web browsing, and moving picture delivery, we failed to observe significant differences between 2G and 3G services. Perhaps a changeover is now occurring from 2G services to 3G, while even progressive 3G subscribers fail to make full use of new 3G services.

V. CONCLUSION

This paper investigated the demand for mobile telephone services including 3G. We particularly focused on the demand substitutability between mature 2G services and emerging 3G services. Two main conclusions are obtained. First, there is a clear distinction between 2G and 3G services for values of price elasticity. 3G services are more price-elastic than 2G services. This conclusion demonstrates that 3G service is still in the process of full-scale diffusion, and new 3G subscribers are currently more sensitive to price changes than 2G subscribers. Second, turning to the analysis of functions such as e-mail, Web browsing, and moving picture delivery, we failed to discover distinct evidence to show that 3G subscribers make full use of new 3G services. However, due to the rapidly changing trends in mobile telephone services, market developments deserve careful consideration and study.

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Table I

BASIC STATISTICS OF DATA

(i) Classified by alternatives

Standard	Provider	Observations	Monthly Expenditure	Call Time (minutes)	Mail No.	Web Browsing	Picture	Movie	TV Telephone
3G	NTT DoCoMo	124	¥7,349.1	48.2	21.7	72	17	12	9
	Ratio (%)	18.1%				58.1%	13.7%	9.7%	7.3%
	KDDI (au)	133	¥5,643.8	36.4	19.2	75	24	16	0
	Ratio (%)	19.4%				56.4%	18.0%	12.0%	0.0%
2G	NTT DoCoMo	202	¥5,835.7	34.5	19.7	105	24	---	---
	Ratio (%)	29.4%				52.0%	11.9%	---	---
	KDDI (au+Tu-ka)	56	¥4,021.8	22.2	16.0	24	2	---	---
	Ratio (%)	8.2%				42.9%	3.6%	---	---
	Vodafone	136	¥5,208.0	25.4	23.1	63	18	---	---
	Ratio (%)	19.8%				46.3%	13.2%	---	---
PHS	Total	36	¥3,404.9	28.3	8.8	6	1	---	---
	Ratio (%)	5.2%				16.7%	2.8%	---	---

(ii) Classified by standard

Standard	Observations	Monthly Expenditure	Call Time (minutes)	Mail No.	Web Browsing	Picture	Movie	TV Telephone
3G	257	¥6,466.6	42.1	20.4	147	41	28	9
Ratio (%)	37.5%				57.2%	16.0%	10.9%	3.5%
2G	394	¥5,361.2	29.6	20.3	192	44	---	---
Ratio (%)	57.4%				48.7%	11.2%	---	---
PHS	36	¥3,404.9	28.3	8.8	6	1	---	---
Ratio (%)	5.2%				16.7%	2.8%	---	---

(iii) Classified by Provider

Provider	Observations	Monthly Expenditure	Call Time (minutes)	Mail No.	Web Browsing	Picture	Movie	TV Telephone
NTT DoCoMo	326	¥6,411.4	39.7	20.5	177	41	12	9
Ratio (%)	50.2%				54.3%	12.6%	3.7%	2.8%
KDDI	189	¥5,163.2	32.2	18.3	99	26	16	0
Ratio (%)	29.1%				52.4%	13.8%	8.5%	0.0%
Vodafone	136	¥5,208.0	25.4	23.1	63	18	---	---
Ratio (%)	19.8%				46.3%	13.2%	---	---

Note 1: Figures of *Ratio (%)* in the *Observations* column denote the choice ratio in each classification.

Note 2: Figures of *Ratio (%)* in the Web Browsing, Picture, Movie, TV Telephone columns denote the choice ratio of the number of subscribers using these functions to the number of subscribers in each alternative.

Table II

SEPARATION OF MONTHLY EXPENDITURE INTO FLAT RATE AND USAGE CHARGES

	Monthly Expenditure	Flat Rate	Call Charge
NTT 3G	¥7,349.0	¥6,081.7	¥1,267.3
		468.635	235.361
KDDI 3G	¥5,643.8	¥4,675.1	¥968.7
		314.800	124.743
NTT 2G	¥5,848.1	¥4,582.8	¥1,265.3
		265.253	137.341
KDDI 2G	¥4,021.8	¥3,234.5	¥787.3
		315.728	181.267
Vodafone 2G	¥5,208.0	¥4,648.7	¥559.3
		294.447	147.904
PHS	¥3,405.0	¥2,760.6	¥644.4
		370.575	227.809

Note 1: The figures in the upper row are calculated at sample means.

Note 2: The figures in the lower row indicate standard errors.

Table III

ESTIMATION RESULTS

Observations	687
Log likelihood	-1137.5517

Variables		Estimates	Standard Error	t-value
Random Parameter				
3G	**Mean**	2.0315	0.8730	2.3270
	Standard Deviation	0.2313	0.4207	0.5500
2G	**Mean**	1.6736	0.8335	2.0080
	Standard Deviation	0.2543	0.4796	0.5300
NTT	**Mean**	0.5129	0.4144	1.2380
	Standard Deviation	2.3814	1.4595	1.6320
KDDI	**Mean**	-3.8664	2.9478	-1.3120
	Standard Deviation	7.8455	5.5727	1.4080
Non random Parameter				
Flat Rate 3G		-0.0002	0.0001	-2.7050
Flat Rate 2G		-0.0001	0.0000	-2.4700
Flat Rate PHS		0.0003	0.0003	0.8990
Call Time 3G		-0.0007	0.0041	-0.1770
Call Time 2G		-0.0031	0.0039	-0.7810
Mail No. 3G		0.0407	0.0169	2.4110
Mail No. 2G		0.0392	0.0159	2.4620
Web 3G		1.6514	0.5316	3.1070
Web 2G		1.4313	0.5130	2.7900
Picture Data 3G		1.5231	1.1201	1.3600
Picture Data 2G		1.0718	1.0884	0.9850
Movie Data 3G		1.7735	0.5466	3.2450

Table IV

PRICE ELASTICITIES

		Choice Probability					
		NTT 3G	**KDDI 3G**	**NTT 2G**	**KDDI 2G**	**Vodafone 2G**	**PHS**
Price	**NTT 3G**	**-0.783**	0.067	0.471	0.055	0.213	0.203
	KDDI 3G	0.032	**-0.564**	0.026	0.436	0.035	0.032
	NTT 2G	0.194	0.022	**-0.303**	0.025	0.091	0.085
	KDDI 2G	0.011	0.156	0.010	**-0.231**	0.013	0.016
	Vodafone 2G	0.076	0.025	0.079	0.027	**-0.283**	0.200

Table V

E-MAIL ELASTICITIES

		Choice Probability					
		NTT 3G	**KDDI 3G**	**NTT 2G**	**KDDI 2G**	**Vodafone 2G**	**PHS**
E-mail	**NTT 3G**	**0.467**	-0.043	-0.286	-0.035	-0.132	-0.070
	KDDI 3G	-0.026	**0.423**	-0.022	-0.322	-0.028	-0.011
	NTT 2G	-0.287	-0.036	**0.447**	-0.039	-0.149	-0.056
	KDDI 2G	-0.019	-0.289	-0.021	**0.420**	-0.026	-0.012
	Vodafone 2G	-0.105	-0.037	-0.118	-0.038	**0.368**	-0.146

Table VI

WEB BROWSING ELASTICITIES

		Choice Probability					
		NTT 3G	**KDDI 3G**	**NTT 2G**	**KDDI 2G**	**Vodafone 2G**	**PHS**
Web Browsing	**NTT 3G**	**0.511**	-0.047	-0.307	-0.037	-0.148	-0.089
	KDDI 3G	-0.029	**0.450**	-0.022	-0.343	-0.030	-0.013
	NTT 2G	-0.277	-0.032	**0.413**	-0.031	-0.127	-0.050
	KDDI 2G	-0.018	-0.277	-0.017	**0.398**	-0.022	-0.012
	Vodafone 2G	-0.106	-0.036	-0.101	-0.033	**0.340**	-0.133

Table VII

MOVING PICTURE ELASTICITIES

		Choice Probability					
		NTT 3G	**KDDI 3G**	**NTT 2G**	**KDDI 2G**	**Vodafone 2G**	**PHS**
Moving picture	**NTT 3G**	**0.074**	-0.015	-0.039	-0.003	-0.025	-0.010
	KDDI 3G	-0.009	**0.057**	-0.003	-0.031	-0.005	-0.002