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Simultaneous Measurement of Time and Risk Preferences: Stated Preference Discrete Choice Modeling Analysis Depending on Smoking Behavior

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SIMULTANEOUS MEASUREMENT OF TIME AND RISK PREFERENCES:

STATED PREFERENCE DISCRETE CHOICE MODELING ANALYSIS DEPENDING ON SMOKING BEHAVIOR

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Abstract: Measuring time and risk preferences and relating them to economic behaviors are important topics in behavioral economics. This paper deals with these problems in two points. First, we develop a new method to simultaneously measure the rate of time preference and the coefficient of risk aversion. Second, we analyze individual-level relationship between preference parameters and cigarette smoking. First, we conclude that current smokers are more impulsive than non-smokers with respect to both delay and probability discounting. Heavy smokers are the most impulsive, while ex-smokers are the most patient. Second, there is no difference in risk and time preferences between male and female smokers and between male and female non-smokers. On the other hand, risk and time preferences are significantly different between male smokers and non-smokers and between female smokers and non-smokers.

Keywords: rate of time preference, coefficient of risk aversion, conjoint analysis, mixed logit model

JEL classifications: D81, D91, I12

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1. INTRODUCTION

In behavioral economics, it is becoming increasingly important to measure preference parameters regarding time and risk and to analyze relationship between preference parameters and economic behaviors, including smoking. Currently, economic psychology is expected to provide significant insights for such fields as consumer choice theory and public policy. The purpose of this paper is to develop a new method to simultaneously measure time and risk preferences and to investigate the relationship between preference parameters and smoking behavior.

Looking at the relevant literatures, many studies have examined the economic-psychological effects of smoking behavior. In general, time preference is measured by time discounting tasks, while risk preference is derived from probability discounting tasks. For the former, respondents choose between small but immediate and large but delayed rewards. Impulsivity is defined as a preference for the small but immediate alternative. For the latter, respondents choose between small but certain and large but risky rewards. Impulsivity is defined as a preference for the large but risky alternative (Mitchell 1999).

Since smoking remains a serious public health issue, it is important to clarify how time and risk preferences are linked to such addictive behaviors as smoking at the individual level. Previous experimental research analyzed this problem by measuring time and risk preferences separately. Research on time preference reported that smokers were more impulsive than non-smokers; namely, smokers more frequently chose sooner-smaller reward over later-larger reward[1]. Examples include Mitchell (1999), Bickel et al. (1999), Odum et al. (2002), Baker et al. (2003), Reynolds et al. (2004), and Ohmura et al. (2005)[2]. Furthermore, Reynolds et al. (2004) reported a significant positive correlation between the number of cigarettes smoked per day and a delay discounting rate. Ohmura et al. (2005) suggested that both the frequency of nicotine self-administration as well as the dosage were positively associated with greater delay

[1]Some research found the opposite: smokers exhibited lower discount rates (Chesson and Viscusi 2000).

[2]Note that impulsive discounting may be more related to adolescents trying cigarettes than to becoming regular smokers (Reynolds et al. 2003, Sato and Ohkusa 2003).

discounting. Turning to the research on risk preference, it remains ambiguous whether smoking and impulsive probability discounting are related. Mitchell (1999), Reynolds et al. (2003), and Ohmura et al. (2005) reported negligible correlations between them[3]. Further detailed research on the relationship between time/risk preferences and smoking behaviors is required[4]. Specifically, we must investigate the interaction of time and risk preferences based on the measures of smoking. The innovation introduced in the present paper is the classification of smoking into three categories based on the Fagerström Test for Nicotine Dependence (FTND) (Heatherton et al. 1991) and, more importantly, measure the rate of time preference and the coefficient of risk aversion by the dependence category.

Time and risk preferences are the two main points of view in behavioral economics. Many attempts have been made to measure the rate of time preference and the coefficient of risk aversion. Interestingly, Prelec and Lowenstein (1991) argued that the discounted utility model (time preference) and the expected utility model (risk preference) have similar structures regarding anomalies[5]. Nevertheless, as Rachlin and Siegel (1994) suggested, the nature of the interaction between time and risk preferences has remained controversial. Barsky et al. (1997) measured preference parameters relating to risk tolerance and intertemporal substitution and analyzed their interaction with "risky" behaviors, including smoking, drinking, noninsurance, and stock speculation. However, most previous studies measured time and risk preferences separately, which is analytically unsatisfactory. Preference parameters must be simultaneously measured regarding delay and probability discounting.

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[3]Reynolds et al. (2004) indicated that although smokers were more impulsive than non-smokers in time and risk preferences, delay discounting was a stronger predictor of smoking than probability discounting.

[4]Other delay-discounting research has shown that children are more impulsive than adults (Green et al. 1994, 1996); males are more impulsive than females (Kirby and Markovic 1996); pathological gamblers and drug-dependent populations are more impulsive than the general population (Alessi and Petry 2003, Petry 2001, Bickel and Marsch 2001).

[5]Most recently, Bommier (2006) has developed a theoretical model that makes the links between preferences over lotteries on length of life and intertemporal choice.

A few studies have tried to integrate the measurements of time and risk preferences. Examples include Rachlin et al. (1991), Keren and Roelofsma (1995), Anderhub et al. (2001), and Yi et al. (2006). However, there is still room to improve both the methodology and results[6]. A promising approach is to simultaneously measure time and risk preferences based on such modern microeconometrics method as conjoint analysis and discrete choice model analysis. The purpose of this paper is to simultaneously measure the rate of time preference and the coefficient of risk aversion at the individual level by using Stated Preference Discrete Choice Model (SPDCM) analysis[7].

The main conclusions of this paper can be summarized in two points. First, we analyze the relationship between smoking and time/risk preferences. As a result, smokers are more impulsive in delay discounting than non-smokers. Furthermore, heavy smokers have the highest rate of time preference among current smokers, while ex-smokers have a lower rate of time preference than never-before smokers. Second, we investigate which is more closely related to differences in preference parameters, smoking or gender differences. The results show that gender differences are not linked to differences in time and risk preferences for either smokers or non-smokers. On the other hand, smoking is significantly related to differences in time and risk preferences for both males and females.

The paper is organized as follows. Section 2 explains the method of sampling data and discuses the data characteristics. Section 3 introduces this paper's conjoint analysis. Section 4 proposes discounted and expected utility models for estimating parameters, and Section 5 portrays a mixed logit model analysis. After displaying basic statistics and estimation results in Section 6, the relationship between smoking and time/risk

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[6]Furthermore, it is important to investigate which is psychologically more fundamental, time or risk preference. At this point, opinions are divided into two camps. Some think that probabilistic discounting is a result of delay discounting (Rachlin et al. 1986, 1991), while others argue that delay discounting reflects the inherent uncertainty in the delay to a reward (Green and Myerson 1996, Stevenson 1986).

[7]Many SPDCM studies have appeared in the field of applied economics. For example, Hall et al. (2002) provides an excellent survey on SPDCM in the field of health economics. Also, Tsuge et al. (2005) is interesting because it applies the SPDCM analysis of risk preference.

preferences are investigated in Section 7. In Section 8, conditional parameters are examined at the individual level. Section 9 gives concluding remarks.

2. DATA SAMPLING METHOD

In this section, we first explain the data sampling method and then the data characteristics. We surveyed Japanese adult registered with a consumer monitor investigative company (whose total number of monitors is about 220,000). Data sampling was performed in the following three stages. First, we randomly drew 10,000 respondents from the monitors and classified them as current or non-smokers[8]. Non-smokers were divided into never-before and ex-smokers. Based on FTND, current smokers were classified into heavy (H), moderate (M), and light (L) smokers. FTND is composed of the following six questions (Heatherton et al. 1991).

1. How soon after you wake up do you smoke your first cigarette? (1) Within 5 minutes (3 points), (2) 6-30 minutes (2 points), (3) 31-60 minutes (1 points), (4) After 60 minutes (0 points)
2. Do you find it difficult to refrain from smoking in places where it is forbidden e.g. in churches, at the library, in cinema, etc.? (1) Yes (1 points), (2) No (0 points)
3. Which cigarette would you hate most to give up? (1) The first one in the morning (1 points), (2) All others (0 points)
4. How many cigarettes/day do you smoke? (1) 10 or less (0 points), (2) 11-20 (1 points), (3) 21-30 (2 points), (4) 31 or more (3 points)
5. Do you smoke more frequently during the first hours after waking than during the rest of the day? (1) Yes (1 points), (2) No (0 points)
6. Do you smoke if you are so ill that you are in bed most of the day? (1) Yes (1 points), (2) No (0 points)

[8]The definition of a current smoker is somebody who has been smoking for one month or more and has smoked at least 100 cigarettes so far.

By aggregating the responses, we defined respondents with 0 to 3 points as low nicotine dependence (L-smokers), 4 to 6 points as moderate nicotine dependence (M-smokers), and 7 and over as high nicotine dependence (H-smokers). Consequently, the ratios are 37% for L-smokers, 42% for M-smokers, and 21% for H-smokers, respectively.

Retuning to the data sampling, at the second stage, we surveyed a random sample of 200 respondents from the five categories (H-, M-, L-, never-, and ex-smokers) and asked them about smoking. The ratio of female smokers at the first stage was 40%, which is higher than the national ratio for adult Japanese female smokers (23%) according to a 2004 survey of Ministry of Health, Labor, and Welfare. Therefore, we set the female ratio of smokers at the second stage to correspond to national figures (23%): 30% for L-smokers, 23% for M-smokers, and 15% for H-smokers. At the third stage, we collected replies from the conjoint analysis regarding time and risk preferences from around 70% of respondents and measured the rate of time preference and the coefficient of risk aversion based on the replies of the conjoint analysis. Note that JPY150 (US$1.4, given JPY110=US$1) was paid to respondents who replied FTND, and JPY500 (US$4.5) was paid to respondents who replied the conjoint questionnaire for recompenses. Table 1 summarizes the demographics of the sample data.

<Table 1>

3. CONJOINT ANALYSIS

In this section, we explain conjoint analysis, a stated preference method that we carried out on 692 respondents sampled at the third stage to simultaneously measure time and risk preferences. Conjoint analysis assumes that a service is a profile composed of attributes. The purpose of the analysis is to construct a profile composed of a palette of introduced attributes. If we include too many attributes and levels, respondents have difficulty answering the questions. On the other hand, if we include too few, the description of alternatives becomes inadequate. After carrying out several pretests, we finally determined the attributes and their levels.

The alternatives, attributes, and levels set in this research are given as follows:

Alternative 1

Reward, probability, and delay are fixed across profiles.

Reward: JPY100,000 (US$909), Winning probability: 100%, Time delay: None.

Alternative 2:

Reward, probability, and delay vary across profiles.

Reward is either JPY150,000 (US$1,364), JPY200,000 (US$1,818), JPY250,000 (US$2,273), or JPY300,000 (US$2,727).

Winning probability is either 40%, 60%, 80%, or 90%.

Time delay is either 1 month, 6 months, 1 year, or 5 years.

Since the number of profiles becomes unwieldy if we consider all possible combinations, we adopt an orthogonal planning method to avoid this problem (see Louviere et al. 2000 Ch. 4 for details). Figure 1 depicts a representative questionnaire covering profiles and attributes. We asked eight questions per respondent and used a stratified random sampling method (explained in Section 2) that totaled 1,112 samples for never-before smokers, 1,192 for ex-smokers, 1,000 for H-smokers, 1,016 for M-smokers, and 1,216 for L-smokers.

<Figure 1>

4. DISCOUNTED AND EXPECTED UTILITY MODELS

In this section, we explain discounted and expected utility models that form the basis for estimating the rate of time preference and the coefficient of risk aversion. Let a utility of alternative j be V_j (reward$_j$, probability$_j$, time delay$_j$). The exponential discounted utility model and the (linear in probability) expected utility model are used for the functional form of V_j[9]. Specifically, we write

[9]As is commonly known, the exponential discounted utility model was advocated by Samuelson (1937) and axiomatically defined by Koopmans (1960) and Fishburn and

Discounted utility: exp(-t*time delay$_j$)*utility(reward$_j$)

given that t is a time preference parameter

Expected utility[10]: probability$_j$*utility(reward$_j$).

Accordingly, rewriting V_j, we obtain

V_j(reward$_j$, probability$_j$, time delay$_j$)

= exp(-t*time delay$_j$)*probability$_j$ *utility(reward$_j$).

At this point, we simply specify the functional form of utility as the r-th power of reward. Such a utility function is called the constant relatively risk-averse form, where the coefficient of relative risk aversion is denoted by 1-r. Taking logarithms of both sides, we obtain

Ln V_j(reward$_j$, probability$_j$, time delay$_j$)

=-t*time delay$_j$+ probability$_j$ +r*reward$_j$.

Two points are noted here: first, the higher the time-impatient (myopic) value is, the larger t is; second, since a risk averse attitude means 1-r ([0,1], the more risk-averse, the larger 1-r is.

One of the main objectives of behavioral economics is discovering and elucidating anomalies. The most famous anomaly in time preference is hyperbolic discounting, where the rate of time preference decreases with time delay (Frederick, Lowenstein, and O'Donoghue 2002). Two well-known anomalies in risk preference are certainty effect and loss aversion (Kahneman and Tversky 1979). Many models have been put forward to account for these anomalies. However, this paper will measure the rate of time preference and the coefficient of relative risk aversion based on the standard discounted and expected utility models. This is firstly because both the constant rate of time preference and the coefficient of relative risk aversion are still providing good benchmarks, and therefore it is difficult to compare preference parameters based on other general models with the preceding observations[11]. Secondly, some models

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Rubinstein (1982). The expected utility model is attributed to Von Neumann and Morgenstern (1953).

[10]If we consider index j the state of nature, $j=1,\ldots,J$, expected utility is written as $\sum_{j=1,\ldots,J}$ probability$_j$*utility(reward$_j$). Note that we simply assume here that one alternative has only one state of nature other than the state of zero reward.

[11]Rubinstein (2003) interestingly argued that the same type of evidence, which rejected

explaining anomalies may be compatible with the standard model by a simple transformation of variables. For example, if setting psychological time as a logarithm of physical time, the exponential discounted model with respect to physical time can be transformed into a hyperbolic discounted model for psychological time (Takahashi 2005).

5. MIXED LOGIT MODEL

This section describes our econometric model. Conditional logit (CL) models, which 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 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 it cannot deal with the distribution of parameters at the individual level (Ben-Akiva, Bolduc, and Walker 2001). Consequently, the most prominent model is a mixed logit (ML) that accommodates differences in variance of random components (or unobserved heterogeneity)[12]. They are flexible enough to overcome the limitations of CL models by allowing random taste variation, unrestricted substitution patterns, and the correlation of random terms over time (McFadden and Train 2000).

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

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the exponential discounted utility model, could just as easily reject hyperbolic discounted utility model as well.

[12]ML models are also called random parameter models if focusing on the distribution of parameters, or as error component models if focusing on flexible substitution patterns (Revelt and Train 1998, Brownstone and Train 1999).

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

which is the normal logit form, given parameter β, the observable portion of utility function V_{ni}, and alternatives *j=1, …, 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

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

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

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

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.

In the form of linear-in-parameter, the utility function can be written as

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

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

Since 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 (co-)variance of parameter density function $f(\beta \mid \theta)$. ML choice probability is approximated through the simulation method. More specifically, 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

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

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.

We can also calculate the estimator of the conditional mean of the random parameters, conditioned on individual specific choice profile y_n (see Revelt and Train 2000 for details), which is given as

$$h(\beta \mid y_n) = \frac{P(y_n \mid \beta) f(\beta)}{\int P(y_n \mid \beta) f(\beta) d\beta} \ .$$

In what follows, we assume that preference parameters regarding time and risk follow normal distribution as follows:

TIME=-*t* (therefore, the rate of time preference is represented by -TIME)

RISK=*r* (therefore, the coefficient of relative risk aversion is represented by 1-RISK)

Accordingly, we can demonstrate variety in parameters at the individual level. Here we use the MSL method for estimation by setting 100 Halton draws[13]. Furthermore, since a respondent repeatedly completes eight questionnaires in the conjoint analysis, we consider the data panel data. Thus, we apply a standard random effect method in which random draws are repeatedly reused for the same respondent.

6. BASIC STATISTICS AND ESTIMATION RESULTS

[13]Louviere et al. (2000 p. 201) suggest that 100 replications are normally sufficient for a typical problem involving five alternatives, 1,000 observations, and up to 10 attributes (also see Revelt and Train 1998). The adoption of Halton sequence draw is an important problem to be examined (Halton 1960). Bhat (2001) found that 100 Halton sequence draws are more efficient than 1,000 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 need to be investigated further (Train 2003).

This section shows the basic statistics and estimation results. We begin with the basic statistics. Table 2 presents the proportion where Alternative 1 (default) is chosen, and the average values of the attributes of Alternative 2 where this is chosen. Smokers are classified into heavy (H), moderate (M), and light (L), and non-smokers are divided into never-before and ex-smokers. Looking at the proportion of times when Alternative 1 is chosen, the figures are identical (64.1%) for both smokers and non-smokers. On the other hand, smokers tend to choose quicker, riskier, and larger rewards than non-smokers in the case Alternative 2 is chosen.

<Table 2>

Let us move on to the estimation results given in Table 3. Having assumed that random parameters are distributed normally, each parameter has mean and standard-deviation (S.D.) estimates. Furthermore, estimation results are reported for smokers (H-, M-, and L-smokers) and non-smokers (never-before and ex-smokers) separately. As for the time-preference parameter TIME, all mean estimates are statistically significant based on t values, and standard deviation estimates are statistically significant except ex-smokers at the 1% significant level. As for the risk preference parameter RISK, all mean estimates are statistically significant based on t values at the 1% significant level, and standard deviation estimates are statistically significant at least at the 10% significant level, except L- and never-before smokers.

<Table 3>

7. TIME PREFERENCE, RISK AVERSION, AND SMOKING BEHAVIORS

In this section, the rate of time preference and the coefficient of relative risk aversion are simultaneously measured based on estimation results. The results are presented in Table 4.

<Table 4>

We begin by examining the rate of time preference. The higher the rate of time preference is, which is defined as -TIME, the more time-impatient (myopic) is the result. The main findings can be summarized as follows:

- Smokers are more time-impatient than non-smokers; the rate of time preference of the former (0.0664) is higher than that of the latter (0.0447).
- Heavy smokers are the most time-impatient among smokers; they have the highest rate of time preference (0.0693).
- Ex-smokers are more time-patient than never-before smokers; the rate of time preference of the former (0.0390) is lower than that of the latter (0.0516).

Our finding that smokers are more impulsive in delay discounting than non-smokers is consistent with preceding observations (Mitchell 1999, Bickel et al. 1999, Odum et al. 2002, Baker et al. 2003, Reynolds et al. 2004, Ohmura et al. 2005)[14]. As expected, heavy smokers are the most impulsive in delay discounting. Note that ex-smokers are more time-patient than never-before smokers, implying that successful smoking cessation may be related to patience[15].

Let us move on to the coefficient of relative risk aversion. The higher the coefficient is, defined as 1-RISK, the more risk-averse the result is. The main findings can be summarized as follows:

- Smokers are more risk-prone than non-smokers; the coefficient of relative risk aversion of the former (0.0896) is lower than that of the latter (0.3001)[16].
- Heavy smokers are the most risk-prone among smokers; they have the lowest coefficient of relative risk aversion (0.0443).

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[14]It is not necessarily a long-established hypothesis that smoking is positively correlated with impulsive delay discounting. Famous research by Fuchs (1982) reported weak relations between them, for example.

[15]The success rate of smoking cessation is around 50%, and, furthermore, the heavier the nicotine-dependency, the lower the success rate (Akkaya et al. 2006).

[16]Note that since the coefficients of relative risk aversion for smokers and non-smokers lie in the interval [0,1], both smokers and non-smokers are still classified as risk-averse types.

- Ex-smokers are more risk-averse than never-before smokers; the coefficient of relative risk aversion of the former (0.3539) is higher than that of the latter (0.2381).

Although many studies have investigated the relationship between smoking and attitudes toward risk, the issue is still inconclusive (Mitchell 1999, Reynolds et al. 2003, Ohmura et al. 2005). It follows from our simultaneous measurement of the rate of time preference and the coefficient of risk aversion that smokers are more risk-prone and more time-impatient than non-smokers; furthermore, heavy smokers are the most risk-prone, while ex-smokers are the most risk-averse. It is in line with our intuitions that a strongly nicotine-dependent person is insensitive to risk, while one who has successfully stopped smoking is sensitive to risk, since smoking is a large risk factor causing serious diseases including lung cancer (Chaloupka and Warner 2000).

The above results mark a breakthrough in the research of the interaction between smoking behavior and time/risk preferences. At this point, two reservations should be mentioned.

First, although Table 4 compares the rates of time preference and the coefficients of relative risk aversion depending on smoking, we need to verify whether preferences truly differ depending on smoking. As such, we statistically investigate whether preferences, expressed as parameters, are equal between different groups by using the likelihood ratio (LR) test in the following procedure. Let *L(A)* and *L(B)* be the estimated log likelihood function values for groups A and B; furthermore, let *L(A+B)* be the value of the estimated log likelihood function for the pooled data; then we obtain the test statistic of $-2[L(A+B)-(L(A)+L(B))]$, which is chi-squared (χ^2) distributed (see Louviere et al. 2000, p. 244). Table 5 shows the results in which the critical value of $\chi^2(d.f.=4, p=0.05)$ is 9.488. If a test statistic is larger than the critical value, we can conclude that time and risk preferences statistically differ between groups A and B. The main results can be summarized as follows:

- A statistically significant difference in time and risk preferences exists between smokers and non-smokers.
- A statistically significant difference in time and risk preferences does not exist depending on nicotine dependence among smokers.
- A statistically significant difference in time and risk preferences does not exist between never-before smokers and ex-smokers.

In conclusion, at least, current smoking or non-smoking significantly influences time and risk preferences.

<Table 5>

Second, since this research only investigated the relationship between smoking and time/risk preferences, we reserve judgment about their causality. Namely, we cannot determine here whether an impulsive person tends to smoke or a smoker tends to become impulsive. A detailed study of causality lies outside the scope of this paper. We consider this the most important area for future research.

8. CONDITIONAL DISTRIBUTIONS AT INDIVIDUAL LEVEL

In an ML model, we can indicate varieties of individual preferences by standard deviations of random parameters. As explained in Section 5, we can also calculate the estimator of the conditional mean of random parameters based on the Bayes theorem (see Revelt and Train 2000). Figure 2 displays conditional distributions of the rate of time preference and the coefficient of risk aversion for smokers and non-smokers. We observe that preferences vary at the individual level.

<Figure 2>

In this section, we further investigate the effects of smoking and gender on time and risk preferences, based on conditional distributions at the individual level. In the previous section we concluded that smokers were more impulsive than non-smokers in both delay and probability discounting. However, according to a 2004 survey of Ministry of Health, Labor, and Welfare, the percentage of adult male Japanese smokers is 43.3% and 12.0% for Japanese females. When discussing the difference in preferences between smokers and non-smokers, the difference in smoking rates by gender should be considered (Kirby and Markovic 1996).

At this point, we calculate the rates of time preference and the coefficients of relative risk aversion for male smokers/non-smokers and female smokers/non-smokers as well as for smoking male/female and non-smoking male/female. Then, we carry out a Welch-t test regarding the difference in mean values and show the results in Table 6. The main points can be summarized as follows:

- Smoking males and smoking females do not differ statistically significantly in time preference, whereas smoking females are more risk-averse than smoking males.
- Similarly, non-smoking males and non-smoking females do not differ statistically significantly in both time and risk preferences.
- On the other hand, male smokers and non-smokers statistically differ in both time and risk preferences. The same result applies to female smokers and non-smokers.

Consequently, smoking, not gender, is significantly linked with differences in time and risk preferences[17].

<Table 6>

9. CONCLUDING REMARKS

Measuring preference parameters regarding time and risk and applying them to economic behavior analysis are important topics in behavioral economics. This paper tried to contribute to these fields in two ways. First, we measured simultaneously the rate of time preference and the coefficient of risk aversion that have so far been addressed separately in the literature. These were measured by using a mixed logit model that can display individual-level variety in preferences. Second, we scrutinized the relationship between time/risk preferences and smoking, in part reinforcing observations of preceding research and in part reaching new findings.

There are two major conclusions in this paper. First, smokers are more impulsive in both delay and probability discounting than non-smokers. Furthermore, heavy smokers

[17]However, taking into consideration the fact that the percentage of adult Japanese males who smoke is much higher than female smokers, we may indirectly say that a difference in time and risk parameters exists between the sexes. We need to consider the specific Japanese cultural and social contexts behind the large gap in smoking rates between the sexes. This is a question for future research.

tend to be more impulsive, while ex-smokers are more patient than never-before smokers. Second, female smokers (female non-smokers) were not observed significantly different from male smokers (male non-smokers) in time preference, while male smokers (female smokers) are significantly different from male non-smokers (female non-smokers) in time and risk preferences.

Finally, we point out some problems that remain unsolved. First, we have not covered any detailed analysis of causality between preferences and smoking. Second, we only dealt with smoking, but in the future we should analyze such addictive behaviors as drinking, gambling, and substance abuse. Third, we should carry out international comparisons to analyze whether the conclusions obtained in this paper hold in different cultures and countries. We consider these issues potential topics for future research.

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TABLE 1: SAMPLE DATA

The 1st-stage sampling

	No. of samples	Sample ratio	Sub-sample ratio	Female ratio	Average age
Sample	10,816	---	---	51%	40.0
Non-smokers	7,632	71%	---	56%	39.7
(1) Never-before smokers	6,089	56%	80%	60%	38.4
(2) Ex-smokers	1,546	14%	20%	38%	45.1
Smokers	3184	29%	---	40%	40.6
(1) H-smokers	671	6%	21%	38%	43.4
(2) M-smokers	1,340	12%	42%	38%	40.8
(3) L-smokers	1,173	11%	37%	43%	38.8

The 2nd-stage sampling

	No. of samples	Sample ratio	Sub-sample ratio	Female ratio	Average age
Sample	1,022	---	---	34%	41.1
Non-smokers	406	40%	---	50%	40.7
(1) Never-before smokers	203	20%	50%	66%	40.2
(2) Ex-smokers	203	20%	50%	35%	41.3
Smokers	616	60%	---	23%	41.3
(1) H-smokers	205	20%	33%	15%	44.2
(2) M-smokers	206	20%	33%	23%	40.4
(3) L-smokers	205	20%	33%	30%	39.3

The 3rd-stage sampling

	No. of samples	Sample ratio	Sub-sample ratio	Female ratio	Average age
Sample	692	---	---	35%	40.2
Non-smokers	288	42%	---	50%	39.6
(1) Never-before smokers	139	20%	48%	65%	36.1
(2) Ex-smokers	149	22%	52%	37%	42.8
Smokers	404	58%	---	25%	40.7
(1) H-smokers	125	18%	31%	18%	43.8
(2) M-smokers	127	18%	31%	21%	39.9
(3) L-smokers	152	22%	38%	34%	38.8

FIGURE 1: REPRESENTATIVE QUESTIONNAIRE

	ALTERNATIVE 1	ALTERNATIVE 2
REWARD	JPY 100,000	JPY 250,000
TIME DELAY	NOW	1 MONTH LATER
WINNING PROBABILITY	100%	80%
	↓	↓
CHOOSE ONE		

TABLE 2: BASIC STATISTICS

	Smokers	H-smokers	M-smokers	L-smokers	Non-smokers	Never-smokers	Ex-smokers
The ratio of Alt 1 chosen	64.1%	63.9%	63.6%	64.9%	64.1%	63.6%	64.5%
	Averages	Averages	Averages	Averages	Averages	Averages	Averages
Time delay (per month)	10.232	9.972	10.311	10.384	11.011	10.941	11.078
Ln probability	-0.232	-0.243	-0.235	-0.221	-0.228	-0.228	-0.227
Ln reward	12.370	12.371	12.373	12.366	12.355	12.350	12.361

Note: Averages are of Alt 2 chosen.

TABLE 3: ESTIMATION RESULTS

	Smokers		H-smokers		M-smokers		L-smokers		Non-smokers		Never-smokers		Ex-smokers	
No. of Samples	3232		1000		1016		1216		2304		1112		1192	
LL Max	-1664.532		-512.547		-525.702		-624.071		-1220.735		-587.972		-630.015	
LL(0)	-2240.2517		-693.1472		-704.238		-842.867		-1597.011		-770.780		-826.231	
Pseudo R2	0.257		0.261		0.254		0.260		0.236		0.237		0.237	
	Coeff./S.E.		Coeff./S.E.		Coeff./S.E.		Coeff./S.E.		Coeff./S.E.		Coeff./S.E.		Coeff./S.E.	
TIME (MEAN)	-0.0664 0.0068	***	-0.0693 0.0133	***	-0.0611 0.0115	***	-0.0669 0.0105	***	-0.0447 0.0054	***	-0.0516 0.0084	***	-0.0390 0.0064	***
RISK (MEAN)	0.9104 0.0714	***	0.9557 0.1408	***	0.9230 0.1295	***	0.8496 0.1102	***	0.6999 0.0785	***	0.7619 0.1076	***	0.6461 0.1152	***
TIME (S.D.)	0.0398 0.0061	***	0.0388 0.0121	***	0.0347 0.0110	***	0.0423 0.0091	***	0.0222 0.0062	***	0.0321 0.0082	***	0.0126 0.0103	
RISK (S.D.)	0.3030 0.1622	*	0.5526 0.2003	***	0.4028 0.2405	*	0.0442 0.2793		0.4203 0.1476	***	0.0288 0.3312		0.6368 0.1533	***

Note: Coefficients in the upper row, Standard errors (S.E.) in the lower row, *** at the 1% significant level, ** at the 5% significant level, *at the 10% signifivcant level.

TABLE 4: TIME PREFERENCE AND RISK AVERSION

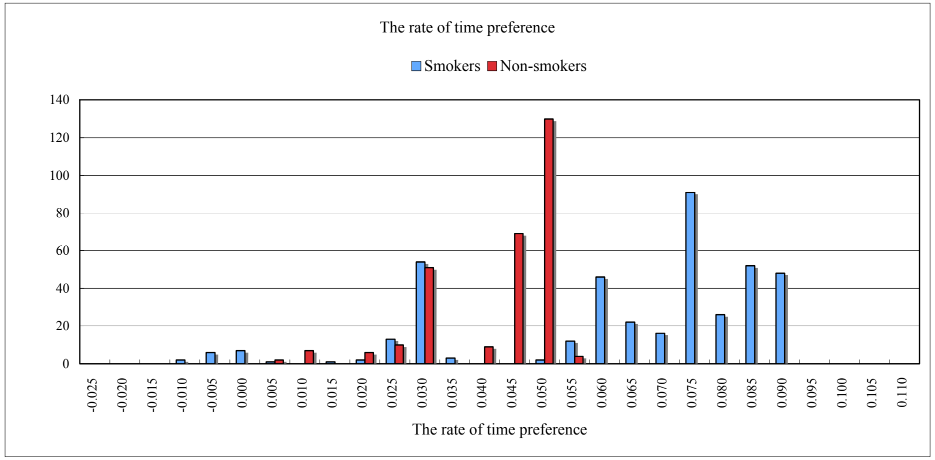
	Smokers	H-smokers	M-smokers	L-smokers	Non-smokers	Never-smokers	Ex-smokers
The rate of time preference	0.0664	0.0693	0.0611	0.0669	0.0447	0.0516	0.0390
The coefficient of relative risk aversion	0.0896	0.0443	0.0770	0.1504	0.3001	0.2381	0.3539

TABLE 5: LR TEST OF JOINT PREFERENCE EQUALITY

	Test statistic	Critical value	Results
Smokers vs. Non-smokers	15.851	9.488	Rejected
Smokers: H-smokers vs. M-smokers vs. L-smokers	4.424	9.488	Not rejected
Non-smokers: Never-smokers vs. Ex-smokers	5.496	9.488	Not rejected

Note: The critical value i $\chi 2$ (d.f.=4,p=0.05).

FIGURE 2: CONDITIONAL DISTRIBUTIONS OF RANDOM PARAMETERS



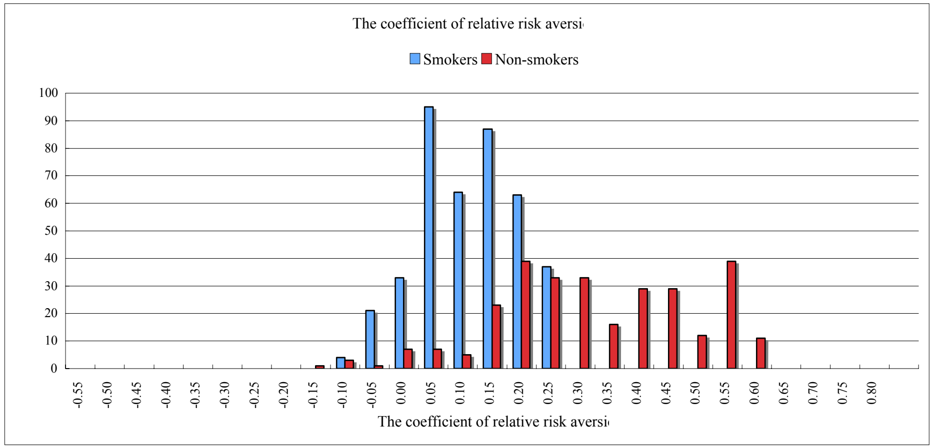


TABLE 6: CONDITIONAL DISTRIBUTIONS AND GENDER DIFFERENCE

		Smokers		Non-smokers	
		Male	Female	Male	Female
The rate of time preference (per month)	Mean	0.0668	0.0652	0.0435	0.0454
	S.D.	0.0240	0.0256	0.0118	0.0098
The coefficient of relative risk aversion	Mean	0.0813	0.1042	0.2975	0.3115
	S.D.	0.0859	0.0752	0.1607	0.1616

		Welch-t value	p value
Smokers: Male vs. Female	Time preference	0.5500	0.5820
	Relative risk aversion	2.5520	0.0110
Non-smokers: Male vs. Female	Time preference	1.4370	0.1510
	Relative risk aversion	0.7390	0.4600
Male: Smokers vs. Non-smokers	Time preference	13.7415	0.0000
	Relative risk aversion	15.1068	0.0000
Female: Smokers vs. Non-smokers	Time preference	7.4194	0.0000
	Relative risk aversion	13.4714	0.0000