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# Ⅲ. 研究成果の刊行物・別刷

Addiction

RESEARCH REPORT

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# A cohort study to examine whether time and risk preference is related to smoking cessation success

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## ABSTRACT

**Aim** To identify whether time and risk preference predicts relapse among smokers trying to quit. **Design** A cohort study of smokers who had recently started to quit. Time and risk preference parameters were estimated using a discrete choice experiment (DCE). **Participants** A total of 689 smokers who began quitting smoking within the previous month. **Measurements** Time discount rate, coefficient of risk-aversion measured at study entry and duration of smoking cessation measured for 6 months. **Findings** In the unadjusted model, Cox's proportional hazard regression showed that those with a high time discount rate were more likely to relapse [hazard ratio: 1.18, 95% confidence interval (CI): 1.11–1.25]. A high coefficient of risk-aversion reduced the hazard of relapse (0.96, 0.96–0.97). When adjusted for other predictors of relapse (age, gender, self-efficacy of quitting, health status, mood variation, past quitting experience, the use of nicotine replacement therapy, nicotine dependence), the hazard ratios of time discount rate and the coefficient of risk-aversion is 1.17 (95% CI: 1.10–1.24) and 0.98 (95% CI: 0.97–0.99), respectively. **Conclusions** Those who emphasize future rewards (time–patient preference) and those who give more importance to rewards that are certain (higher risk-aversion) were significantly more likely to continue to abstain from smoking.

**Keywords** Abstinence, discrete choice experiment, mixed logit model, relapse, risk-aversion coefficient, smoking cessation, survival analysis, time preference rate.

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## INTRODUCTION

Economists focus upon rational models of addiction. They suggest that smokers and non-smokers differ in their preferences concerning delay and probability. These differences arise because of the differences in the weight they place upon present and future rewards and those with certainty and risk. Theoretically, smokers who are concerned about the future health consequences of smoking will choose not to smoke, while those who weigh current benefits more heavily and discount future consequences will choose to smoke [1]. Among people attempting to quit smoking, those who have a strong preference for short-term rewards would be less likely to endure the discomfort of abstinence from smoking to gain the long-term rewards of improved health. Similarly, those who have a strong preference for risk would be less likely to stop smoking because they underestimate the expected damage to their health.

To gain the same satisfaction or utility, future and risky gains are weighed less than present and certain gains. This procedure is referred to as discounting, and discounting is of two types: time and probability. Time discounting is used commonly in health economic modelling of health-care interventions [2].

With regard to smoking behaviour, the parameters of time and probability discounting have been measured empirically. Much research on time preference has reported that smokers, in comparison to non-smokers, prefer smaller rewards obtained earlier over larger rewards at some more distant point in the future [3,4]. The results of research on risk preference are controversial [3,5], however, and there is insufficient evidence to determine whether smoking is associated with a risk-prone preference.

To our knowledge, only a few studies have investigated the association of time and risk preference parameters to the success of smoking cessation. The role of time preference in smoking cessation has been studied among pregnant women [6], adolescents [7] and in a laboratory model of abstinence reinforcement [8]. These studies found that impulsive time discounting was associated with increased relapse. However, they did not investigate relationships between probability discounting and smoking cessation.

The main aim of this paper was to identify the role of time and risk preference parameters in smoking cessation on the basis of a longitudinal survey of those who tried to stop smoking.

## METHODS

### Data

From May 2007 onwards, we asked the smoking status of 85 900 Japanese adults registered with a consumer monitoring company. We recruited into the study all 854 respondents who answered that they had stopped smoking within the previous month. Next, they were asked to reply to a questionnaire that included a discrete choice experiment (DCE) for measuring the time- and risk-preference parameters. We also collected data on potential predictors of quitting success: Fagerström Test for Nicotine Dependence (FTND) [9], age, gender, self-efficacy of quitting, health status, mood variations, past quitting experience and the use of nicotine replacement therapy. After excluding invalid respondents and respondents who had smoked fewer than 100 cigarettes in their life [10], we obtained 689 participants (response rate = 80.7%).

In the second stage, we followed these participants by monthly questionnaire for 5 months. On each occasion, participants were asked to answer the question, 'Are you still trying to stop smoking? Please answer "no" if you have smoked "even-a-puff" since the first recruitment'. Among those who answered positively, the same question was asked 1 month later. Those who answered negatively were defined to be smoking relapse cases, and the follow-up was terminated. In the case of those who did not respond, the same question was sent 3 days later as a reminder and 1 month later if they had not responded. After the fifth month, those who remained to answer positively were defined as successful smoking cessation cases.

This research was approved by the ethical committee of Nara Women's University.

### Measuring time and risk preferences

Questionnaire surveys are used to measure the time discount rate empirically. A simple example is: 'How many pounds that you can gain after 1 year are equivalent to £100 that you can gain now?'. In this case, the time discount rate is 10% if £110 after 1 year is equivalent to £100 now. The higher the amount, the larger the time discount rate, and the more weight a person places upon present rewards. A larger time discount rate corresponds to more time-impatience or myopic time preference.

Similarly, we can measure the risk preference parameter by asking: 'How many pounds would you want to gain with a probability of 50% that you feel would be equivalent to a certain gain of £100?'. The higher the amount, the larger the weight they place upon rewards that they are certain to gain. We can determine the coefficients of risk-aversion based on the answers to these questions. A larger coefficient of risk-aversion corresponds to a more risk-averted preference.

Using the above-mentioned questions to measure time and risk preferences is problematic. First, the open-ended questions that enquire about the amounts of money impose a cognitive load upon respondents. Answering choice questions similar to daily choices is easier than answering questions based upon an amount of money. Secondly, time and risk preferences are correlated with each other [11]. For example, questions related to future rewards inevitably include risk questions if one believes that future rewards always involve risks. Hence, measuring two preference parameters separately cannot help to distinguish time and risk preferences.

To solve these problems, we measure simultaneously the time and risk preference parameters using DCE. This technique has been applied in health-care settings [12,13], and the outcomes have revealed that DCE results have internal validity and consistency [14].

### Discrete choice experiment

DCE is an attribute-based measure of benefit. Any good or service is described on the basis of the bundle of its attributes or characteristics. The extent to which an individual values a good or a service is evaluated on the basis of the selection of hypothetical choices imitating the daily decision-making process.

If we include too many attributes and levels, then respondents face difficulties in answering the questions. If, on the other hand, we include too few the description of the alternatives becomes inadequate. After conducting several pretests, we determined the alternatives, attributes and their levels as follows:

*Alternative 1*: reward, probability and delay are fixed across profiles.
Reward: JPY100 000 (US$100); winning probability: 100%; time delay: none.

*Alternative 2*: reward, probability and delay vary across profiles.
Reward: either JPY150 000 (US$1500), JPY200 000 (US$2000), JPY250 000 (US$2500) or JPY300 000

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

**Figure 1** Representative questionnaire

(US$3000); winning probability: 40, 60, 80 or 90%; time delay: 1 month, 6 months, 1 year or 5 years.

Because the number of profiles becomes unwieldy if we consider all possible combinations ($4^3 = 64$ in this case), we adopted an orthogonal planning method to avoid this problem [15]. Figure 1 depicts a representative questionnaire covering the profiles and attributes. Respondents were asked to choose eight different pairs in the levels of each attribute of alternative 2.

Details of how to measure the two preferences using DCE are provided elsewhere [16]. The summary of the method for the estimation of individual preference parameters is presented in the Appendix.

### Survival analysis

To analyse whether the time and preference parameters predict the success of smoking cessation, we used Cox's proportional hazard model with a time-dependent covariate [17]. We then adjusted these models for potential confounders, the predictors of quitting reported above. Stata 10 (Stata Corp., College Station, TX, USA) was used for the survival analysis. We used NLOGIT3.0 (Econometric Software, Inc., Plainview, NY, USA) for analysis of the DCE and for estimation of the time and risk parameters. We calculated 95% confidence intervals (CI) and considered $P < 0.05$ to be significant.

## RESULTS

The mean age was 34.7, and the proportion of females was 44.6%. The mean FTND was 3.5, lower than in treatment-seeking populations but similar to other population samples of smokers [18].

The sample mean of the time discount rate is 0.07 (95% CI: 0.02–0.09) per month. Those with a higher time discount prefer short-term rewards. The coefficient of risk-aversion (sample mean = 0.19) increases as preference becomes more risk-averse. A person's risk preference is classified as being risk-averse if the coefficient of risk-aversion is positive; as risk-neutral, if it is zero; and as risk-prone, if it is negative. Most individuals (529, 76.8%) were risk-averse (Table 1).

Overall, 321 (46.6%) smokers succeeded in quitting smoking at the time of the final survey that was conducted 5 months later. The relapse rate reduced over time.

**Table 1** Descriptive statistics.

| | | *Total (n = 689)* |
|---|---|---|
| Age (years) | 20–29 | 34.3% |
| | 30–39 | 39.3% |
| | 40–49 | 18.1% |
| | Mean (SD) | 34.7 (10.1) |
| Gender | Female | 44.6% |
| Previously tried to quit | | 18.3% |
| Use of nicotine replacement therapy | | 19.7% |
| Self-efficacy of quitting | | 5.38 (1.29) |
| Health status (before quitting) | | 2.93 (0.88) |
| Mood variation | | 3.09 (0.80) |
| FTND | | 3.52 (2.71) |
| Time discount rate | | 0.07 (0.26) |
| Coefficient of risk-aversion | | 0.19 (0.21) |

Self-efficacy of quitting: on the basis of the answer to 'How certain are you that you would succeed'? The responses were graded from 1 (extremely weak) to 7 (extremely strong) [34]. Health status: based on the response to the question 'How did you feel about your health before this quitting attempt'? The responses were graded from 1 (extremely well) to 5 (extremely bad). Mood variations: based on the answer to the question 'How has your mood changed after quitting? Has it become comfortable or irritating'? The answers were graded from 1 (very comfortable) to 5 (very irritated). FTND: Fagerström Test for Nicotine Dependence; SD: standard deviation.

The conditional probability of failure was 21.2%, 11.4%, 7.9%, 4.7% and 4.7% from the first month to the fifth month, respectively. Eighty-one (11.8%) respondents were lost to follow-up.

The unadjusted model showed that participants who emphasized future rewards measured by a 1% point higher time discount rate were significantly more likely to relapse to smoking (hazard ratio: 1.18, 95% CI: 1.11–1.25, $P < 0.001$). Participants who had a higher coefficient of risk-aversion by 0.01 were less likely to relapse, with a hazard ratio of 0.963 (0.96–0.97, $P < 0.001$).

After controlling for possible predictors of cessation, future time preference and risk-aversion remained associated significantly with relapse to smoking. Hazard ratios of time discount rate and risk-aversion coefficient are 1.17 (95% CI: 1.10–1.24, $P < 0.001$) and 0.984 (95% CI: 0.97–0.99, $P = 0.001$), respectively. Note that as the changes in time discount rate and risk-aversion coefficient are extremely small, we estimated the hazard ratios based on the values multiplied by 100.

**Table 2** Cox's proportional hazard model for relapse to smoking with time-dependent variables.

| | *β coefficient* | *Hazard ratio* | *95% CI* |
|---|---|---|---|
| Time-invariant terms | | | |
| Time discount rate (×100) | 0.158*** | 1.172 | 1.10–1.24 |
| Coefficient of risk-aversion (×100) | −0.016*** | 0.984 | 0.97–0.99 |
| Age (years) | | | |
| 30–39 | 0.011 | 1.011 | 0.76–1.34 |
| 40–49 | 0.277 | 1.319 | 0.93–1.86 |
| 50 and over | −0.186 | 0.831 | 0.52–1.33 |
| Gender (female dummy) | −0.433* | 0.649 | 0.41–1.02 |
| Self-efficacy of quitting | −0.140*** | 0.869 | 0.79–0.95 |
| Health status | 0.016 | 1.016 | 0.89–1.16 |
| Mood variation | 0.100 | 1.105 | 0.94–1.30 |
| Inexperienced quitter | 1.209*** | 3.351 | 1.61–7.00 |
| Nicotine replacement therapy | −0.380** | 0.684 | 0.49–0.96 |
| FTND | | | |
| Middle (4 ≤ FTND score ≤ 6) | −0.080 | 0.923 | 0.71–1.19 |
| High (7 ≤ FTND score ≤ 10) | −1.065** | 0.345 | 0.14–0.87 |
| Time-variant terms | | | |
| Coefficient of risk-aversion (×100) | −0.011*** | 0.989 | 0.98–0.99 |
| Gender (female dummy) | 0.187* | 1.206 | 1.00–1.46 |
| Inexperienced quitter | −0.322** | 0.725 | 0.56–094 |
| FTND | | | |
| High (7 ≤ FTND score ≤ 10) | 0.379** | 1.461 | 1.06–2.01 |
| No. of samples | 689 | | |
| Log likelihood | −1693.608 | | |

Time-variant terms refer to the interaction terms between the time-dependent variables and the time elapsed after the beginning of the follow-up. Levels of statistical significance are reported at 1% (***), 5% (**) and 10% (*) significance levels, respectively. CI: confidence interval; FTND: Fagerström Test for Nicotine Dependence.

We estimated a Cox's proportional hazard model with time-dependent variables (Table 2). We tested the assumption of proportional hazard for each variable using Shoenfeld residuals [17]; those with a high coefficient of risk-aversion are more likely to continue to abstain from smoking. The effect intensified over time (0.989, 0.98–0.99, $P < 0.001$).

## DISCUSSION

This study has shown that time preference and risk preference are associated with failure or success of a quit attempt. People with a future orientation and people who were risk-averse were more likely to succeed in quitting.

Conventional hypothetical money choice tasks and scales such as the Zimbardo Time Perspective Inventory [19] do not cope with time and risk preferences at the same time. We assumed the utility function, including both the exponential time discounted and the (linear in probability) expected utility model. Then, we estimated simultaneously the time discounting rate and the coefficient of risk-aversion. Therefore, our estimation methods are consistent with the economic models concerning both delay and probability discounting.

The main result of this study is that time and risk parameters predict significantly the success of the attempts of those who had already quit for up to 1 month at baseline. Previous literature from economics and psychology determined the difference in time preference between smokers and non-smokers [3,4,20–22]. We showed that time and risk preferences were important among smokers attempting to quit smoking. In terms of time preference, the result that lower time discounting is associated with prolonged abstinence from smoking is consistent with the results of previous research [6–8]. The current study also detected a significant association between risk preference with smoking cessation, using a new population not based upon a clinical trial.

A higher time discount rate or a more myopic time preference has been found in not only nicotine dependence but also in other forms of addiction such as substance use, alcohol and pathological gambling [23]. However, it is not clear as to what originates first, myopic preference or addiction [24]. A detailed investigation of causality is required.

Previous studies have also found that time and risk preferences were associated with social behaviour such as buying life insurance policies and being involved in speculative investment [25], as well as in preventive behaviours such as exercise and a healthy diet [26]. Detailed social and medical history-taking, on the basis of which one can infer a patient's time and risk preferences, may be helpful in providing effective cessation support by determining the risk of relapse among quitters.

There is some evidence that individual time preference rates are associated with education and income levels [27,28]. Therefore, if one receives more education, one's time preference rate might decrease, thereby lowering the likelihood of relapse. Governments might consider education as an effective countermeasure for stopping smoking.

There are several limitations to our research. First, the overall success rate of cessation for 5 months is 46.6% in this research. Only 3–5% of self-quitters are reported to achieve prolonged abstinence for 6–12 months, and most relapses are reported to occur the within first 8 days after a given quit attempt [29]. This research analysed mainly long-term abstinence for quitters who had abstained successfully from smoking in the first week. More research on predictors of successful quitting will be needed to focus upon the initial period of smoking cessation.

Secondly, it is unclear whether our sample is typical of all smokers who try to quit in Japan. The participants participating in these kinds of studies might be more motivated than average smokers. However, it is difficult to see how the selection processes involved in participating in a study such as this would lead to a spurious association between time and risk preference and relapse.

Thirdly, smoking status and continued cessation from smoking were based upon self-report. However, biochemical validation is not generally advised in low-contact population studies such as this, because there is little incentive for participants to deceive the researcher about their true smoking status. [30]. Further studies are needed to examine how these and other cognitive factors affect the likelihood of overcoming addictive disorders.

## Declarations of interest

None.

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## APPENDIX

Here, we explain the discounted and expected utility models that form the basis for estimating the time preference rate and risk-aversion coefficient. Let the utility of alternative $i$ be $V_i$ (reward$_i$, probability$_i$, timedelay$_i$). The exponential discounted utility model and the (linear in probability) expected utility model are used for the functional form of $i$ be $V_i$.

$$\text{Discounted utility: } \exp(-TIME \times \text{timedelay}_i) \times \text{utility}(\text{reward}_i),$$

where parameter *TIME* denotes the time discount rate.

$$\text{Expected utility: probability}_i \times \text{utility}(\text{reward}_i).$$

Accordingly, rewriting $V_i$, we obtain

$$V_i(\text{reward}_i, \text{probability}_i, \text{timedelay}_i) = \exp(-TIME \times \text{timedelay}_i) \times \text{probability}_i \times \text{utility}(\text{reward}_i).$$

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

$$\ln V_i(\text{reward}_i, \text{probability}_i, \text{timedelay}_i) = -TIME \times \text{timedelay}_i + \ln \text{probability}_i + RISK \times \ln \text{reward}_i.$$

Two points should be noted here: first, a greater level of impatience implies a larger *TIME*; secondly, because a risk-averse attitude means $1-RISK \in [0,1]$, a greater level of risk-aversion implies a larger 1–*RISK*.

In the estimation of the discrete choice model, conditional logit (CL) models, which assume independent and identical distribution (IID) of random error terms, have been used widely in past studies. However, the independence of irrelevant alternatives (IIA) property derived from the IID assumption of the CL model is too strict to allow flexible substitution patterns. The most prominent approach is a mixed logit (ML) model that accommodates differences in the variance of random components (or unobserved heterogeneity). These models are flexible enough to overcome the limitations of CL models by allowing random taste variation, unrestricted substitution patterns and the correlation of random error terms over time [31].

Assuming that parameter $\beta_n$ is distributed with density function $f(\beta_n)$[32], the ML specification allows for repeated choices by each sampled decision maker in such a way that the coefficients vary over people but are constant over choice situations for each person. The logit probability of decision maker $n$ choosing alternative $i$ in choice situation $t$ is expressed as:

$$L_{nit}(\beta_n) = \prod_{t=1}^{T} \left[ \exp(V_{nit}(\beta_n)) \Big/ \sum_{j=1}^{J} \exp(V_{njt}(\beta_n)) \right],$$

which is the product of normal logit formulas, given parameter $\beta_n$, the observable portion of utility function $V_{nit}$, and alternatives $j = 1, \ldots, J$ in choice situations $t = 1, \ldots, T$. Therefore, the ML choice probability is a weighted average of logit probability $L_{nit}(\beta_n)$ evaluated at parameter $\beta_n$ with density function $f(\beta_n)$, which can be written as:

$$P_{nit} = \int L_{nit}(\beta_n) f(\beta_n) d\beta_n.$$

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

$$U_{nit} = \gamma' x_{nit} + \beta_n' z_{nit} + \varepsilon_{nit},$$

where $x_{nit}$ and $z_{nit}$ denote observable variables, $\gamma$ denotes a fixed parameter vector, $\beta_n$ denotes a random parameter vector and $\varepsilon_{nit}$ denotes an independently and identically distributed extreme value (IIDEV) term.

Because the ML choice probability is not expressed in closed form, simulations need to be performed for the ML model estimation [32]. We can also calculate the estimator of the conditional mean of the random parameters, conditioned on individual specific choice profile $y_n$, given as:

$$h(\beta|y_n) = [P(y_n|\beta) f(\beta)] \Big/ \int P(y_n|\beta) f(\beta) d\beta.$$

Here, we assume that the preference parameters regarding time and risk follow normal distributions:

*TIME* (time discount rate),
*RISK* (coefficient of relative risk-aversion represented by 1−*RISK*).

The random utility that person $n$ obtains from choosing alternative $i$ in choice situation $t$ can be written as follows:

$$U_{nit} = -\alpha * TIME * timedelay_{nit} + \alpha * \ln probability_{nit} + \alpha * RISK * \ln reward_{nit} + \varepsilon_{nit},$$

where $\alpha$ is a scale parameter that is not separately identified from free parameters and is normalized to one [33].

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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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Measuring time and risk preferences and relating them to economic behaviors are important topics in behavioral economics. We developed a new method to simultaneously measure the rate of time preference and the coefficient of risk aversion. Analyzing the individual-level relationships between preference parameters and cigarette smoking, we conclude that current smokers are more impatient and risk-prone than nonsmokers. Heavy smokers are the most impatient and risk-prone, whereas ex-smokers are the most patient and risk-averse. Among nonsmokers, neither age-related nor gender-related differences were found. On the other hand, risk and time preferences are significantly different according to age and gender for smokers.

## 1. INTRODUCTION

In behavioral economics, measuring preference parameters regarding time and risk and analyzing relationships between preference parameters and economic behaviors, including smoking, are becoming increasingly important. Currently, economic psychology is expected to provide significant insights for such fields as consumer choice theory and public policy. This article develops a new method to simultaneously measure time and risk preferences and investigates the relationship between preference parameters and smoking behavior.

Many studies, including Mitchell (1999), have examined the economic–psychological effects of smoking behavior. Time preference is generally measured by time-discounting tasks, whereas risk preference is derived from probability discounting tasks. For the former, respondents choose between two kinds of rewards: small but immediate and large but delayed. Impatient respondents prefer the small but immediate alternative. For the latter, respondents choose between small but certain and large but risky rewards.

Because smoking remains a serious public health issue, it is important to clarify how time and risk preferences are linked to addictive behaviors at the individual level. Previous experimental research analyzed this problem by separately measuring time and risk preferences. Research on time preference reported that smokers were more impatient than nonsmokers; smokers more frequently chose the earlier–smaller reward over the later–larger reward. 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). 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 the frequency of nicotine self-administration as well as the dosage were positively associated with greater delay discounting. Risk preference research has been unable to determine whether smoking and risk-prone preference is related.

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Mitchell (1999), Reynolds et al. (2003), and Ohmura et al. (2005) reported negligible correlations.[2] Further research on the relationship between time and risk preferences and smoking behaviors is required.[3] In this article, we classified smokers into three categories based on the Fagerström Test for Nicotine Dependence (FTND) (Heatherton et al., 1991) and then measured the rate of time preference and the coefficient of risk aversion by a dependence category.

Time and risk preferences are the two main focuses in behavioral economics. There have been many attempts to measure the rate of time preference and the coefficient of risk aversion. Interestingly, Prelec and Loewenstein (1991) argued that the discounted utility model (time preference) and the expected utility model (risk preference) have similar structures regarding their known anomalies. Nevertheless, as Rachlin and Siegel (1994) suggest, the nature of the interaction between time and risk preferences remains controversial. Barsky et al. (1997) measured preference parameters related to risk tolerance and intertemporal substitution and analyzed interaction with "risky" behaviors, including smoking, drinking, noninsurance, and stock speculation. Most previous studies measured time and risk preferences separately, which is analytically unsatisfactory. Preference parameters regarding delay and probability discounting must be simultaneously measured.

A few studies have integrated the measurements of time and risk preferences, including 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.[4] Our article simultaneously measures the rate of time preference and the coefficient of risk aversion at the individual level using Stated Preference Discrete Choice Model (SPDCM) analysis.

Our two main conclusions can be summarized as follows. First, we analyzed the relationship between smoking and time and risk preferences and found that smokers are more impatient and risk-prone than nonsmokers. Heavy smokers tend to be more impatient and risk-prone, whereas ex-smokers are more patient and risk-averse than never-before smokers. Second, we investigated whether smoking or gender is more closely related to differences in preference parameters. Our results show that gender differences are not linked to differences in time and risk preferences for nonsmokers. On the other hand, they are significantly related to differences in time and risk preferences for smokers. Similar results are observed for age differences.

This article is organized as follows. Section 2 explains the data sampling method and discusses the data characteristics. Section 3 introduces this article's conjoint analysis. Section 4 proposes discounted and expected utility models for estimating parameters, and Section 5 presents a mixed logit model analysis. After displaying the basic statistics and estimation results in Section 6, the relationship between smoking and time/risk preferences is investigated in Section 7. In Section 8, the influences of individual characteristics on smoking are examined. Finally, Section 9 gives some concluding remarks.

## 2. DATA SAMPLING METHOD

In this section, we explain the data sampling method and the data characteristics. We surveyed Japanese adults registered with a consumer monitor investigative company (with about 220,000 monitors). Data sampling was performed in the following three stages. First, we randomly drew

[2] Reynolds et al. (2004) indicated that although smokers were more impatient and risk-prone than nonsmokers, delay discounting was a stronger predictor of smoking than probability discounting.

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

[4] 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), whereas others argue that delay discounting reflects the inherent uncertainty in the delay to a reward (Stevenson, 1986; Green and Myerson, 1996).

10,000 respondents from the monitors and classified them as current or nonsmokers.[5] Nonsmokers were divided into never-before and ex-smokers. Based on FTND, current smokers were classified as heavy (H), moderate (M), and light (L). 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 point), (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 church, at the library, in cinema, etc.? (1) Yes (1 point), (2) No (0 points)
3. Which cigarette would you hate most to give up? (1) The first one in the morning (1 point), (2) All others (0 points)
4. How many cigarettes/day do you smoke? (1) 10 or less (0 points), (2) 11–20 (1 point), (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 point), (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 point), (2) No (0 points)

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

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%), based on a 2004 survey of the Ministry of Health, Labor, and Welfare. Therefore, we set the ratio of female smokers at the second stage to correspond to the national figure (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 the respondents and measured the time preference rate and the risk-aversion coefficient based on replies to the conjoint analysis. The respondents received a slight remuneration after completing the questionnaire. Table 1 summarizes the demographics of the sample data.

## 3. CONJOINT ANALYSIS

In this section, we explain the 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. The conjoint analysis assumes that a service is a profile composed of 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 the alternatives becomes inadequate. After conducting several pretests, we determined the alternatives, attributes, and levels 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.

[5] A current smoker is defined as somebody who has been smoking for one month or more and has smoked at least 100 cigarettes so far.

TABLE 1

SAMPLE DATA

| | No. of Samples | Sample Ratio | Subsample Ratio | Female Ratio | Average Age |
|---|---|---|---|---|---|
| | | First-stage Sampling | | | |
| Sample | 10,816 | — | — | 51% | 40.0 |
| Nonsmokers | 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 | 3,184 | 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 |
| | | Second-stage Sampling | | | |
| Sample | 1,022 | — | — | 34% | 41.1 |
| Nonsmokers | 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 |
| | | Third-stage Sampling | | | |
| Sample | 692 | — | — | 35% | 40.2 |
| Nonsmokers | 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 |

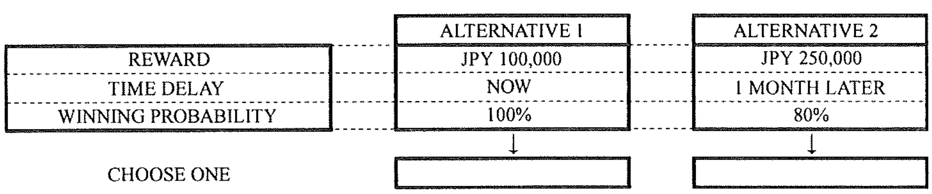



FIGURE 1

REPRESENTATIVE QUESTIONNAIRE

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 40%, 60%, 80%, or 90%.
Time delay is 1 month, 6 months, 1 year, or 5 years.

Because the number of profiles becomes unwieldy if we consider all possible combinations, we adopted 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.

## 4. DISCOUNTED AND EXPECTED UTILITY MODELS

In this section, we explain the discounted and expected utility models that form the basis for estimating the time preference rate and the risk-aversion coefficient. Let a utility of alternative $i$ be $V_i$ (reward$_i$, probability$_i$, time delay$_i$). The exponential discounted utility model and the (linear in probability) expected utility model are used for the functional form of $V_i$:[6]

$$\text{Discounted utility : } \exp(-TIME \times \text{timedelay}_i) \times \text{utility}(\text{reward}_i),$$

where parameter $TIME$ denotes the rate of time preference.

Expected utility:[7] probability$_i$ $*$ utility(reward$_i$).

Accordingly, rewriting $V_i$, we obtain

$$V_i(\text{reward}_i, \text{probability}_i, \text{timedelay}_i) = \exp(-TIME \times \text{timedelay}_i) \\ \times \text{probability}_i * \text{utility}(\text{reward}_i).$$

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

$$\ln V_i(\text{reward}_i, \text{probability}_i, \text{timedelay}_i) = -TIME \times \text{timedelay}_i + \ln \text{probability}_i \\ + RISK \times \ln \text{reward}_i.$$

Two points should be noted here: First, a greater level of impatience implies a larger $TIME$; second, because a risk-averse attitude means $1-RISK \in [0,1]$, a greater level of risk aversion implies a larger $1 - RISK$.

One main objective 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 et al., 2002). Two well-known anomalies in risk preference are certainty effect and loss aversion (Kahneman and Tversky, 1979) for which many models have struggled to account. Nonetheless, this article will measure the rate of time preference and the coefficient of relative risk aversion based on the standard discounted and expected utility models for two reasons. First, both the constant rate of time preference and the coefficient of the relative risk aversion still provide good benchmarks, and therefore comparing preference parameters based on other general models with the preceding observations is difficult.[8] Second, some models explaining anomalies may be compatible with the standard model by a simple transformation of variables. For example, if psychological time is set as a logarithm of physical time, an 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

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

[6] As is commonly known, the exponential discounted utility model was advocated by Samuelson (1937) and axiomatically defined by Koopmans (1960) and Fishburn and Rubinstein (1982). The expected utility model is attributed to Von Neumann and Morgenstern (1953).

[7] If we consider index $s$ the state of nature, $s = 1, \ldots, S$, expected utility is written as $\Sigma_{s=1,\ldots,S}$ probability$_s$ $\times$ utility(reward$_s$). Note that we simply assume here that one alternative has only one state of nature other than the state of zero reward.

[8] Rubinstein (2003) interestingly argued that the same type of evidence, which rejected the exponential discounted utility model, could just as easily reject hyperbolic discounted utility models as well.

strict to allow flexible substitution patterns. A nested logit (NL) model partitions the choice set and allows alternatives to have common unobserved components compared with nonnested 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 et al., 2001). Consequently, the most prominent model is a mixed logit (ML) model that accommodates differences in the variance of random components (or unobserved heterogeneity). These models 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).

Assuming that parameter $\beta_n$ is distributed with density function $f(\beta_n)$ (Louviere et al., 2000; Train, 2003), the ML specification allows for repeated choices by each sampled decision maker in such a way that the coefficients vary over people but are constant over choice situations for each person. The logit probability of decision maker $n$ choosing alternative $i$ in choice situation $t$ is expressed as

$$(1)\qquad L_{nit}(\beta_n) = \prod_{t=1}^{T}\left[\exp(V_{nit}(\beta_n)) \Big/ \sum_{j=1}^{J}\exp(V_{njt}(\beta_n))\right],$$

which is the product of normal logit formulas, given parameter $\beta_n$, the observable portion of utility function $V_{nit}$, and alternatives $j = 1, \ldots, J$ in choice situations $t = 1, \ldots, T$. Therefore, ML choice probability is a weighted average of logit probability $L_{nit}(\beta_n)$ evaluated at parameter $\beta_n$ with density function $f(\beta_n)$, which can be written as

$$(2)\qquad P_{nit} = \int L_{nit}(\beta_n) f(\beta_n)\, d\beta_n.$$

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

$$(3)\qquad U_{nit} = \gamma' x_{nit} + \beta_n' z_{nit} + \varepsilon_{nit},$$

where $x_{nit}$ and $z_{nit}$ denote observable variables, $\gamma$ denotes a fixed parameter vector, $\beta_n$ denotes a random parameter vector, and $\varepsilon_{nit}$ denotes an independently and identically distributed extreme value (IIDEV) term.

Because the ML choice probability is not expressed in closed form, simulations need to be performed for the ML model estimation. Let $\theta$ denote the mean and (co-)variance of parameter density function $f(\beta_n \mid \theta)$. ML choice probability is approximated through the simulation method (see Train, 2003, p. 148, for details). 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, 1998, for details), given as

$$(4)\qquad h(\beta \mid y_n) = [P(y_n \mid \beta) f(\beta)] \Big/ \int P(y_n \mid \beta) f(\beta)\, d\beta.$$

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

*TIME* (rate of time preference)
*RISK* (coefficient of relative risk aversion represented by $1 - RISK$).

The random utility that person $n$ obtains from choosing alternative $i$ in choice situation $t$ can be written as follows:

$$(5)\qquad U_{nit} = -\alpha * TIME \times timedelay_{nit} + \alpha \times \ln\ probability_{nit} + \alpha \times RISK \times \ln\ reward_{nit} + \varepsilon_{nit}$$

TABLE 2
BASIC STATISTICS

| | Smokers | H-smokers | M-smokers | L-smokers | Nonsmokers | Never-smokers | Ex-smokers |
|---|---|---|---|---|---|---|---|
| Ratio of alternative 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 Alternative 2 chosen.

TABLE 3
ESTIMATION RESULTS

| | Smokers | H-smokers | M-smokers | L-smokers | Nonsmokers | Never-smokers | Ex-smokers |
|---|---|---|---|---|---|---|---|
| No. of samples | 3,232 | 1,000 | 1,016 | 1,216 | 2,304 | 1,112 | 1,192 |
| LL Max | −1664.532 | −512.547 | −525.702 | −624.071 | −1220.735 | −587.972 | −630.015 |
| LL(0) | −2240.252 | −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*** | 0.0693*** | 0.0611*** | 0.0669*** | 0.0447*** | 0.0516*** | 0.0390*** |
| | 0.0068 | 0.0133 | 0.0115 | 0.0105 | 0.0054 | 0.0084 | 0.0064 |
| RISK (MEAN) | 0.9104*** | 0.9557*** | 0.9230*** | 0.8496*** | 0.6999*** | 0.7619*** | 0.6461*** |
| | 0.0714 | 0.1408 | 0.1295 | 0.1102 | 0.0785 | 0.1076 | 0.1152 |
| TIME (S.D.) | 0.0398*** | 0.0388*** | 0.0347*** | 0.0423*** | 0.0222*** | 0.0321*** | 0.0126 |
| | 0.0061 | 0.0121 | 0.0110 | 0.0091 | 0.0062 | 0.0082 | 0.0103 |
| RISK (S.D.) | 0.3030* | 0.5526*** | 0.4028* | 0.0442 | 0.4203*** | 0.0288 | 0.6368*** |
| | 0.1622 | 0.2003 | 0.2405 | 0.2793 | 0.1476 | 0.3312 | 0.1533 |

NOTE: Coefficients in the upper row, standard errors (S.E.) in the lower row, *** at the 1% significance level, * at the 10% significance level.

where $\alpha$ is a scale parameter that is not separately identified from free parameters and is normalized to one (Hensher et al., 2005, p. 536).[9]

Accordingly, we can demonstrate variety in the parameters at the individual level with the maximum simulated likelihood (MSL) method for estimation by setting 100 Halton draws.[10] Furthermore, because a respondent repeatedly completes eight questionnaires in the conjoint analysis, the data form a panel, and we can also apply a standard random effect estimation.

## 6. BASIC STATISTICS AND ESTIMATION RESULTS

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 as heavy (H), moderate (M), and light (L), and nonsmokers are divided into never-before and ex-smokers.

Table 3 gives the estimation results. Having assumed that random parameters are distributed normally, each parameter has mean and standard-deviation (SD) estimates. Furthermore,

[9] Louviere et al. (2000, pp. 142–143) showed that variance is an inverse function of the scale as $\sigma^2 = \pi^2/6\alpha^2$. Therefore, associated variance $\sigma^2$ becomes 1.645.

[10] Louviere et al. (2000, p. 201) suggested 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 an ML model.

TABLE 4
TIME PREFERENCE AND RISK AVERSION

| | | Smokers | H-smokers | M-smokers | L-smokers | Nonsmokers | Never-smokers | Ex-smokers |
|---|---|---|---|---|---|---|---|---|
| Time preference (TIME) | Estimates | 0.0664 | 0.0693 | 0.0611 | 0.0669 | 0.0447 | 0.0516 | 0.0390 |
| | S.E. | 0.0068 | 0.0133 | 0.0115 | 0.0105 | 0.0054 | 0.0084 | 0.0064 |
| Relative risk aversion (1 − RISK) | Estimates | 0.0896 | 0.0443 | 0.0770 | 0.1504 | 0.3001 | 0.2381 | 0.3539 |
| | S.E. | 0.0714 | 0.1408 | 0.1295 | 0.1102 | 0.0785 | 0.1076 | 0.1152 |

estimation results are separately reported for smokers (H-, M-, and L-smokers) and nonsmokers (never-before and ex-smokers). For time preference parameter *TIME*, all mean estimates are statistically significant based on $t$ values, and standard deviation estimates are statistically significant, except for ex-smokers at the 1% significance level. For risk preference parameter *RISK*, all mean estimates are statistically significant based on $t$ values at the 1% significance level, and standard deviation estimates are at least statistically significant at the 10% significance level, except for L- and never-before smokers.

## 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.

A higher rate of time preference, defined as *TIME*, implies greater impatience. The main findings can be summarized as follows:

- Smokers are more impatient than nonsmokers; the rate of time preference of the former (0.0664) is higher than the latter (0.0447).
- Heavy smokers are the most impatient among smokers; they have the highest rate of time preference (0.0693).[11]
- Ex-smokers are more patient than never-before smokers; the rate of time preference of the former (0.0390) is lower than the latter (0.0516).

Our finding that smokers are more impatient than nonsmokers is consistent with preceding observations (Bickel et al., 1999; Mitchell, 1999; Odum et al., 2002; Baker et al., 2003; Reynolds et al., 2004; Ohmura et al., 2005). As expected, heavy smokers are the most impatient.[12] Note that ex-smokers are more patient than never-before smokers, implying that successful smoking cessation may be related to patience.[13]

Defined as $1 - RISK$, the higher the coefficient of relative risk aversion, the more risk averse is the result. The main findings can be summarized as follows:

- Smokers are more risk-prone than nonsmokers; the coefficient of the relative risk aversion of the former (0.0896) is lower than the latter (0.3001).[14]

[11] Note here that the estimated rate of time preference is the lowest for those moderately dependent on nicotine. Therefore, we will verify whether preferences truly differ depending on nicotine dependence using the LR test below.

[12] We followed convention in health economics by classifying smokers into three groups depending on FTND scores (see Guillon et al., 2007; Haberstick et al., 2007, for example). However, because the number of classifications and the selection of cut-points may be arbitrary, we need to verify how sensitive our results are to small changes in cut-points (de Leon et al., 2003; Storr et al., 2005). After slightly changing the cut-points to the left and to the right, we verified that higher dependent smokers are more impatient and risk-prone than lower dependent smokers.

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

[14] Because the coefficients of relative risk aversion for smokers and nonsmokers lie in the interval [0,1], both smokers and nonsmokers are still classified as risk-averse types.

TABLE 5
LR TEST OF JOINT PREFERENCE EQUALITY

| | Test Statistics | *P* Values |
|---|---|---|
| Smokers vs. nonsmokers | 15.851 | 0.003 |
| Smokers: H-smokers vs. M-smokers vs. L-smokers | 4.424 | 0.352 |
| Nonsmokers: Never-smokers vs. Ex-smokers | 5.496 | 0.240 |

NOTE: $\chi^2(\text{df} = 4)$ are 13.276 for $P = 0.01$, 9.488 for $P = 0.05$, and 7.779 for $P = 0.1$.

- Heavy smokers are the most risk-prone among smokers; they have the lowest coefficient of relative risk aversion (0.0443).
- Ex-smokers are more risk-averse than never-before smokers; the coefficient of the relative risk aversion of the former (0.3539) is higher than the latter (0.2381).

Although many studies have investigated the relationship between smoking and attitudes toward risk, the issue remains 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 than nonsmokers; furthermore, heavy smokers are the most risk-prone, whereas ex-smokers are the most risk-averse. This reflects our intuition that a strongly nicotine-dependent person is insensitive to risk, whereas one who has successfully stopped smoking is sensitive to risk, because smoking is a large risk factor causing serious diseases, including lung cancer (Chaloupka and Warner, 2000).

However, at this point, two reservations must be mentioned. First, although Table 4 compares how the rates of time preference and the coefficients of relative risk aversion depend on smoking, we need to verify whether preferences truly differ among groups. We statistically investigated whether preferences, expressed as parameters, are equal between different groups using the likelihood-ratio (LR) test. Table 5 summarizes the results as follows:

- A statistically significant difference in time and risk preferences exists between smokers and nonsmokers.
- No statistically significant difference in time and risk preferences exists that depends on nicotine dependence among smokers.
- No statistically significant difference in time and risk preferences exists between never-before and ex-smokers.

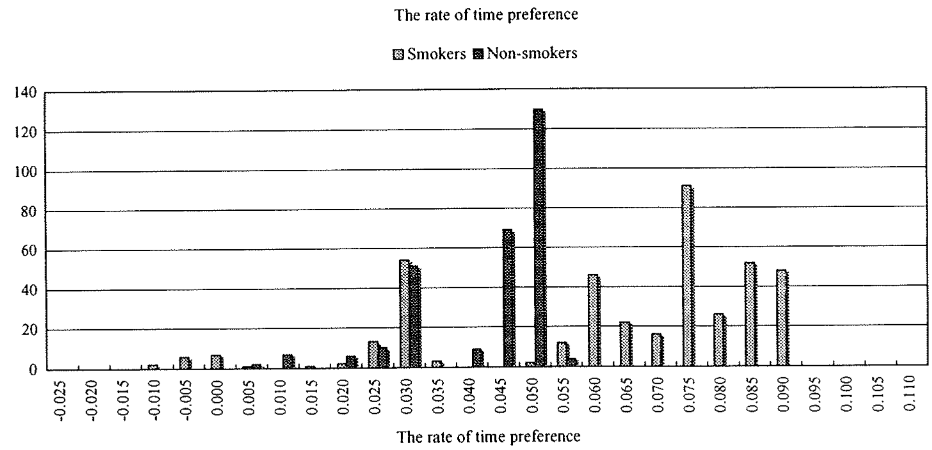
Current smoking or nonsmoking is significantly associated with time and risk preferences.

Second, because this research only investigated the relationship between smoking and time/risk preferences, we reserve judgment about causality because 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 article. We consider this the most crucial area for future research.[15]

## 8. INDIVIDUAL CHARACTERISTICS AND SMOKING

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,

[15] Rimm et al. (1995) discussed that the prevalence of smoking is higher in heavy drinkers than in moderate or nondrinkers, and alcohol consumption is higher in smokers than in nonsmokers. Madden et al. (2000) pointed out a positive genetic correlation between smoking and drinking. Furthermore, Rose et al. (2004) investigated subjective and behavioral interactions among nicotine, ethanol, and nicotinic antagonist mecamylamine. There may be some commonality in the neural pathways mediating the effects of nicotine and ethanol.



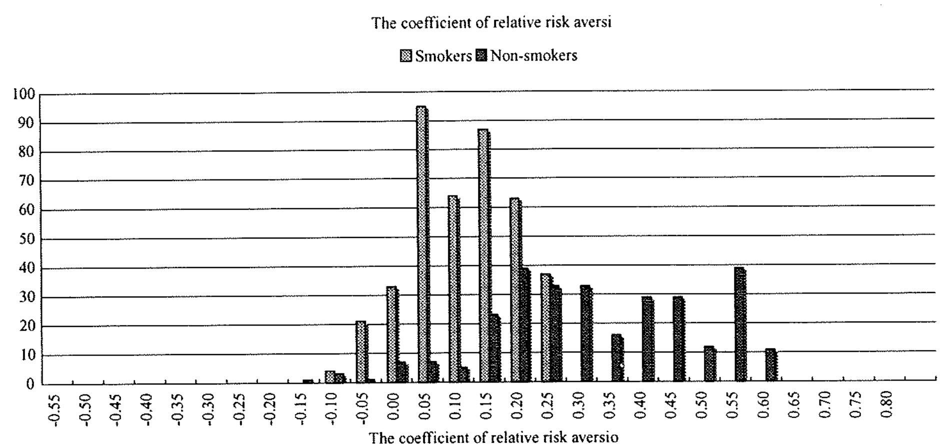




FIGURE 2

CONDITIONAL DISTRIBUTIONS OF RANDOM PARAMETERS

1998). Figure 2 displays the conditional distributions of the time preference rate and the risk-aversion coefficient for smokers and nonsmokers. Preferences vary at individual levels.[16]

We concluded above that smokers were more impatient and risk-prone than nonsmokers. However, according to a 2004 survey conducted by the Ministry of Health, Labor, and Welfare, the percentages of adult male and female Japanese smokers are 43.3% and 12.0%, respectively. When discussing differences in preferences between smokers and nonsmokers, differences in smoking rates by individual characteristics including gender must be considered (Kirby and Markovic, 1996). Thus, we further investigated the differences in time/risk preferences using an LR test between male and female smokers, between male and female nonsmokers, between older (over 50) and younger (less than 50) smokers, and between older and younger nonsmokers.

The estimation results, given in Table 6, are separately reported for male and female smokers, male and female nonsmokers, older and younger smokers, and older and younger nonsmokers. For time preference parameter *TIME*, all mean estimates are statistically significant based on *t* values, and standard deviation estimates are statistically significant except for female

[16] The presence of multiple observations on stated choice responses for each sampled individual means that the potential for correlated responses across observations violates the independence of observation assumptions in classical choice model estimation (Hensher and Greene, 2003). However, because ML models address unobserved heterogeneity by a random parameters specification, the correlation is automatically accommodated through the explicit modeling of preference heterogeneity across choice situations (Daniels and Hensher, 2000).

TABLE 6
ESTIMATION RESULTS (GENDER AND AGE)

| | Male Smokers | Female Smokers | Male Nonsmokers | Female Nonsmokers | Older (50≤) Smokers | Younger (<50) Smokers | Older (50≤) Nonsmokers | Younger (<50) Nonsmokers |
|---|---|---|---|---|---|---|---|---|
| No. of Samples | 2,432 | 800 | 1,144 | 1,160 | 896 | 2,336 | 656 | 1,648 |
| LL Max | −1238.821 | −421.102 | −615.110 | −603.665 | −453.1487 | −1206.547 | −351.471 | −867.609 |
| LL(0) | −1685.734 | −554.518 | −792.960 | −804.051 | −621.0599 | −1619.192 | −454.705 | −1142.307 |
| Pseudo $R^2$ | 0.265 | 0.241 | 0.224 | 0.249 | 0.270 | 0.255 | 0.227 | 0.240 |
| | Coeff./ S.E. | Coeff./ S.E. | Coeff./ S.E. | Coeff./ S.E. | Coeff./ S.E. | Coeff./ S.E. | Coeff./ S.E. | Coeff./ S.E. |
| TIME (MEAN) | 0.0736*** | 0.0468*** | 0.0456*** | 0.0432*** | 0.0753*** | 0.0644*** | 0.0472*** | 0.0448*** |
| | 0.0082 | 0.0102 | 0.0078 | 0.0076 | 0.0131 | 0.0077 | 0.0114 | 0.0063 |
| RISK (MEAN) | 1.0284*** | 0.5951*** | 0.7289*** | 0.6651*** | 1.1631*** | 0.8350*** | 0.6536*** | 0.7130*** |
| | 0.0856 | 0.1269 | 0.1081 | 0.1146 | 0.1540 | 0.0799 | 0.1616 | 0.0898 |
| TIME (S.D.) | 0.0434*** | 0.0275*** | 0.0293*** | 0.0147 | 0.0390*** | 0.0411*** | 0.0298*** | 0.0209*** |
| | 0.0071 | 0.0102 | 0.0085 | 0.0108 | 0.0106 | 0.0069 | 0.0124 | 0.0072 |
| RISK (S.D.) | 0.4139*** | 0.0009 | 0.2719 | 0.5210*** | 0.7134*** | 0.0041 | 0.6377*** | 0.2872 |
| | 0.1531 | 0.3999 | 0.2954 | 0.1783 | 0.1901 | 0.2978 | 0.2274 | 0.2319 |

NOTE: Coefficients in the upper row, standard errors (S.E.) in the lower row, *** at the 1% significance level.

TABLE 7
TIME PREFERENCE AND RISK AVERSION (GENDER AND AGE)

| | | Male Smokers | Female Smokers | Male Nonsmokers | Female Nonsmokers |
|---|---|---|---|---|---|
| Time preference (TIME) | Estimates | 0.0736 | 0.0468 | 0.0456 | 0.0432 |
| | S.E. | 0.0082 | 0.0102 | 0.0078 | 0.0076 |
| Relative risk aversion (1 − RISK) | Estimates | −0.0284 | 0.4049 | 0.2711 | 0.3349 |
| | S.E. | 0.0856 | 0.1269 | 0.1081 | 0.1146 |
| | | Older (50≤) Smokers | Younger (<50) Smokers | Older (50≤) Nonsmokers | Younger (<50) Nonsmokers |
| Time preference (TIME) | Estimates | 0.0753 | 0.0644 | 0.0472 | 0.0448 |
| | S.E. | 0.0131 | 0.0077 | 0.0114 | 0.0063 |
| Relative risk aversion (1 − RISK) | Estimates | −0.1631 | 0.1650 | 0.3464 | 0.2870 |
| | S.E. | 0.1540 | 0.0799 | 0.1616 | 0.0898 |

nonsmokers. For risk preference parameter *RISK*, all mean estimates are statistically significant based on *t* values, but standard deviation estimates are not statistically significant for some cases.

Next the rate of time preference and the coefficient of relative risk aversion were simultaneously measured based on estimation results (Table 7). We compared male/female smokers/nonsmokers and then older/younger smokers/nonsmokers. The main findings can be summarized as follows:

- Male smokers are more impatient and risk-prone than female smokers.
- Male nonsmokers are only slightly more impatient and risk-prone than female nonsmokers.
- Older smokers are more impatient and risk-prone than younger smokers.
- Older nonsmokers are only slightly more impatient than younger nonsmokers. On the other hand, older nonsmokers are only slightly less risk-prone than younger nonsmokers.