

# **A Choice Experiment Model for the Perception of Environmental Risk: A Joint Estimation using Stated Preference and Probability Data**

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## **Abstract**

The purpose of this study was to develop a theoretical model of a choice experiment (CE) under conditions of uncertainty. We used the maximum simulated likelihood method for a joint estimation model using a panel data of stated worst-choice and highest probability. Empirical results were as follows: (1) it is difficult to decompose stated worst-choice data into utility and probability functions; (2) joint estimation using worst-choice and highest probability data can be decomposed into utility and probability functions; (3) estimated WTPs by the usual CE model are significantly different from the ones in the joint model. These results suggest that the usual CE model may be unsuitable in cases of uncertainty, while our joint estimation model between stated worst-choice and highest probability data may be more effective.

## **Keywords**

choice experiments, environmental risk, maximum simulated likelihood method, panel data

JEL Codes: Q26

# **A Choice Experiment Model for the Perception of Environmental Risk: A Joint Estimation using Stated Preference and Probability Data <sup>\*1</sup>**

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## **1 Introduction**

Most environmental disasters have some degree of uncertainty associated with them. For example, an oil spill has associated uncertainties, such as the probability of tanker accidents, the scale of the spill, and the damage incurred by the environment, which depends on the direction of prevailing winds and ocean currents. Contingent valuation (CV) has traditionally been used to estimate the use and non-use value of environmental resources which include environmental risks (Carson et al., 1995). There are some advantages in CV method; however, it is difficult to distinguish the value of each attribute of multi-attribute environmental goods using CV. For example, the damage to natural resources caused by an oil spill includes direct and indirect damage to health, and the effects on coastal ecosystems, commercial fishing, recreational use and shipping. Traditional CV can estimate the total value of protection from oil spills, but it cannot identify the value of each attribute of the damage.

Some economists have recently begun to pay attention to choice experiments (CEs) as a new evaluation technique that might be able to distinguish the value of each component of a multi-attribute environmental commodity. CEs are a multi-attribute, preference-elicitation technique that is widely used in marketing research and transportation (Louviere 1988, Louviere et al., 2000). CEs ask respondents to choose their most preferred alternative from a set of alternatives. Earlier CE studies in environmental economics include Boxall et al. (1996, hunting), Adamowicz et al. (1998, habitat protection), Hanley et al. (1998, environmentally sensitive areas), Garrod and Willis (1998, landfill waste disposal), Rolfe et al. (2000, tropical forest), Carlsson and Martinsson (2001, donations for environmental projects), Gordon et al. (2001, water supply), Bennett et al. (2001, wetlands protection), and Blamey et al. (2001 green product). Although the number of CE studies continues to increase, few have estimated environmental risks.

The purpose of this paper was to develop a theoretical model of CEs under conditions of uncertainty. We used a joint estimation model with stated preference data and probability data to analyze environmental risk. Section 2 provides economic models of CEs under conditions of uncertainty. Section 3 presents an empirical analysis of damage caused by oil spills in Tokyo Bay. Finally, section 4 offers concluding comments.

## **2 Model**

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**Figure.1: Example of Choice Experiment Questions**

Assume that the following three accidents can occur. Which accident do you think is the most likely to occur? Which accident do you regard as the worst?

	Accident 1	Accident 2	Accident 3
Health effects	10,000 people suffer from oil fumes and from headaches	0 people suffer from oil fumes and from headaches	10,000 people suffer from oil fumes and from headaches
Damage to tidelands	76%	21%	10%
Damage to fishing ports	34%	34%	0%
Recovery period	16 years	4 years	2 years
Cleanup costs (tax)	10,000 yen	30,000 yen	5000 yen

Highest possibility is ( )

Worst damage is ( )

### CE Question Format

Figure 1 provides an example of the CE question format used to determine the environmental risk of oil spills. In this example, respondents were introduced to three accident scenarios. Each accident had five attributes: health effects, damaged tidelands, fishing ports, recovery period, and cleanup costs. Respondents were asked to choose the one accident that they thought was most likely to occur (“highest probability”). Furthermore, they were asked to select the one accident that they regarded as the worst. Respondents were allowed to choose the same accident for the highest probability and the worst damage category.

### Economic Model of Worst Choice

The data regarding the highest probability and the worst damage from the responses to the CE questions can be analyzed using a random utility model. When accident  $j$  occurs, the ex-post indirect utility function of the respondent  $i$  is assumed to be  $U_{ij}$ . We assumed that respondents make choices that maximize their expected utility, where the expected utility of accident  $j$  is defined as:

$$E[U_{ij}] = \pi_{ij} \cdot U_{ij} \quad (1)$$

$\pi_{ij}$  is the probabilistic weight of occurrence of accident  $j$ . The expected utility can be represented by

$$E[U_{ij}] = \pi_{ij} \cdot V_{ij} + \varepsilon_{ij} = \pi_{ij} \cdot \beta' \mathbf{x}_{ij} + \varepsilon_{ij} \quad (2)$$

where  $V_{ij}$  is a deterministic component of utility,  $\varepsilon_{ij}$  is a stochastic component,  $\beta$  is the vector of the marginal utility of the attributes and  $\mathbf{x}_{ij}$  is the vector of attributes of accident  $j$ . Assumed that the error terms in equation (2) are distributed independently, identically extreme value (Gumbel distribution) and have variance  $\sigma_\varepsilon^2 \cdot \pi^2/6$ . Then the probability of the worst choice,  $W_{ij}$ , has the closed-form representation:

$$\begin{aligned}
W_{ij} &= \Pr(E[U_{ij}] < E[U_{ik}], \forall k \in \mathbf{C}, k \neq j) \\
&= \frac{\exp\left(-\pi_{ij} \cdot \frac{\beta' \mathbf{x}_{ij}}{\sigma_\varepsilon}\right)}{\sum_{k \in \mathbf{C}} \exp\left(-\pi_{ik} \cdot \frac{\beta' \mathbf{x}_{ik}}{\sigma_\varepsilon}\right)} \tag{3}
\end{aligned}$$

where  $\mathbf{C}$  is a set of accidents ( $\mathbf{C} = \{1, 2, 3\}$ ). The probabilistic weight function of accident  $j$  can be represented by:

$$\pi_{ij} = \phi_{ij} + \eta_{ij} = \alpha' \mathbf{x}_{ij} + \eta_{ij} \tag{4}$$

where  $\phi_{ij}$  is a deterministic component of the probability,  $\eta_{ij}$  is a stochastic component, and  $\alpha$  is the vector of parameters. Assume that  $\eta_{ij}$  is iid extreme value with variance  $\sigma_\eta^2 \cdot \pi^2/6$ . Since we do not know  $\pi_{ij}$ , the probability of the worst choice is integral of (3) over all value of  $\pi_{ij}$ :

$$\begin{aligned}
W_{ij} &= \int \frac{\exp\left(-\pi_{ij} \cdot \frac{\beta' \mathbf{x}_{ij}}{\sigma_\varepsilon}\right)}{\sum_{k \in \mathbf{C}} \exp\left(-\pi_{ij} \cdot \frac{\beta' \mathbf{x}_{ik}}{\sigma_\varepsilon}\right)} f(\eta) d\eta \\
&= \int \frac{\exp\left(-(\alpha' \mathbf{x}_{ij} + \sigma_\eta \mu_{ij}) \cdot \frac{\beta' \mathbf{x}_{ij}}{\sigma_\varepsilon}\right)}{\sum_{k \in \mathbf{C}} \exp\left(-(\alpha' \mathbf{x}_{ik} + \sigma_\eta \mu_{ik}) \cdot \frac{\beta' \mathbf{x}_{ik}}{\sigma_\varepsilon}\right)} f(\mu) d\mu \\
&= \int \frac{\exp\left(-(\hat{\alpha}' \mathbf{x}_{ij} + \mu_{ij}) \cdot \hat{\beta}' \mathbf{x}_{ij}\right)}{\sum_{k \in \mathbf{C}} \exp\left(-(\hat{\alpha}' \mathbf{x}_{ik} + \mu_{ik}) \cdot \hat{\beta}' \mathbf{x}_{ik}\right)} f(\mu) d\mu \\
&= \int \frac{\exp\left(-\hat{\pi}_{ij} \cdot \hat{\beta}' \mathbf{x}_{ij}\right)}{\sum_{k \in \mathbf{C}} \exp\left(-\hat{\pi}_{ik} \cdot \hat{\beta}' \mathbf{x}_{ik}\right)} f(\mu) d\mu
\end{aligned} \tag{5}$$

where  $\mu$  is a random term that is iid extreme value with variance  $\pi^2/6$ ,  $\hat{\alpha}' = \alpha' / \sigma_\eta$ ,  $\hat{\beta}' = (\sigma_\eta \beta') / \sigma_\varepsilon$ ,  $f$  is the density function, and  $\hat{\pi}_{ij} = \hat{\alpha}' \mathbf{x}_{ij} + \mu_{ij}$  is re-scaled probabilistic weight function<sup>\*2</sup>.

While this integral can not be calculated analytically, we can approximate the probability through simulation (Train, forthcoming). (1) Draw a value of  $\mu_{ij}$  from  $f(\mu)$  and calculate the probabilistic weight  $\hat{\pi}_{ij}$ . Label it  $\hat{\pi}_{ij}^r$  where  $r$  is  $r$ -th draw. (2) Calculate the logit formula with this draw. (3) Repeat steps 1 and 2, and average the results. Simulated probability of worst choice is:

$$\tilde{W}_{ij} = \frac{1}{R} \sum_{r=1}^R \frac{\exp\left(-\hat{\pi}_{ij}^r \cdot \hat{\beta}' \mathbf{x}_{ij}\right)}{\sum_{k \in \mathbf{C}} \exp\left(-\hat{\pi}_{ik}^r \cdot \hat{\beta}' \mathbf{x}_{ik}\right)} \tag{6}$$

where  $R$  is the number of draws.

<sup>\*2</sup> This is similar to the choice probability of mixed logit (random parameters logit). Mixed logit allows that the coefficients of observed variables to vary randomly over people. Mixed logit probabilities are the integral of standard logit probabilities over a density of parameters:

$$P_{ij} = \int \frac{\exp(\beta' \mathbf{x}_{ij})}{\sum_{k \in \mathbf{C}} \exp(\beta' \mathbf{x}_{ik})} f(\beta) d\beta$$

## Panel Data

This model can be easily extended repeated choice situation by each respondent. We assume that the probabilistic weight  $\pi_{ij}$  varies over respondent but not over choice situations in each respondent. The re-scaled probabilistic weight of accident  $j$  in choice situation  $t$  by respondent  $i$  is  $\hat{\pi}_{ijt} = \hat{\alpha}' \mathbf{x}_{ijt} + \mu_{ijt}$ . Consider a sequence of accidents for each period,  $\mathbf{j} = \{j_1, j_2, \dots, j_T\}$ . The simulated probability of this sequence of worst choice for the respondent  $i$  is

$$\tilde{W}_{ij} = \frac{1}{R} \sum_{r=1}^R \prod_{t=1}^T \frac{\exp(-\hat{\pi}_{ij,t}^r \cdot \hat{\beta}' \mathbf{x}_{ij,t})}{\sum_{k \in \mathbf{C}} \exp(-\hat{\pi}_{ikt}^r \cdot \hat{\beta}' \mathbf{x}_{ikt})} \quad (7)$$

where subscript  $ij,t$  means that respondent  $i$  chose accident  $j_t$  in period  $t$ . The simulated log-likelihood function of the worst-choice data ( $LL_W$ ) is as follows:

$$LL_W = \sum_i \ln \tilde{W}_{ij} \quad (8)$$

## Joint Estimation

When the error terms  $\eta_{ij}$  of equation (4) follow a iid extreme value distribution with variance  $\sigma_\eta^2 \cdot \pi^2/6$ , the probability that respondents choose accident  $m$  in the highest probability question is:

$$\begin{aligned} P_{im} &= \prod_{t=1}^T \Pr(\pi_{im,t} > \pi_{ikt}, \forall k \in \mathbf{C}, k \neq m) \\ &= \prod_{t=1}^T \frac{\exp\left(\frac{\alpha' \mathbf{x}_{im,t}}{\sigma_\eta}\right)}{\sum_{k \in \mathbf{C}} \exp\left(\frac{\alpha' \mathbf{x}_{ikt}}{\sigma_\eta}\right)} = \prod_{t=1}^T \frac{\exp(\hat{\alpha}' \mathbf{x}_{im,t})}{\sum_{k \in \mathbf{C}} \exp(\hat{\alpha}' \mathbf{x}_{ikt})} \end{aligned} \quad (9)$$

where  $\hat{\alpha}' = \alpha' / \sigma_\eta$ , subscript  $im,t$  means that respondent  $i$  chose accident  $m_t$  in period  $t$ , and  $\mathbf{m} = \{m_1, m_2, \dots, m_T\}$  is a sequence of accidents for each period<sup>\*3</sup>. The log-likelihood function of highest probability data ( $LL_P$ ) then follows:

$$LL_P = \sum_i \ln P_{im}. \quad (10)$$

Stated worst-choice and highest probability data can be analyzed using a joint estimation model (Ben-Akiva and Morikawa, 1990; Adamowicz et al., 1998). A random term ( $\varepsilon$ ) of the expected utility function ( $\pi \cdot \beta' \mathbf{x}$ ) is iid extreme value with variance  $\sigma_\varepsilon^2 \cdot \pi^2/6$ , and a random component ( $\mu$ ) of re-scaled expected utility function ( $\hat{\pi} \cdot \hat{\beta}' \mathbf{x}$ ) is iid extreme value with variance  $\pi^2/6$ . On the other hand, an error term ( $\eta$ ) of the probabilistic weight function ( $\pi$ ) is iid extreme value with variance  $\sigma_\eta^2 \cdot \pi^2/6$ , and a random term ( $\mu$ ) of re-scaled probabilistic weight function ( $\hat{\pi}$ ) is iid extreme value with variance  $\pi^2/6$ . Thus random components of re-scaled expected utility function ( $\hat{\pi} \cdot \hat{\beta}' \mathbf{x}$ ) and re-scaled

<sup>\*3</sup> Note that sum of the re-scaled probabilistic weight over all accidents is not equal to one ( $\sum_j \hat{\pi}_{ij} \neq 1$ ).

probabilistic weight function ( $\hat{\pi}$ ) have same distributions ( $\mu$ ), therefore, the pooling data of stated worst-choice and highest probability can be analyzed jointly<sup>\*4</sup>. The log-likelihood function of this joint model is as follows:

$$\begin{aligned} LL_{W+P} &= LL_W + LL_P \\ &= \sum_i \ln \tilde{W}_{ij} + \sum_i \ln P_{im}. \end{aligned} \tag{11}$$

### 3 Application

This empirical study used survey data concerning hypothetical oil spills in Tokyo Bay. Japan depends on imports for most of its petroleum resources; transportation of petroleum resources by tanker vessels is therefore indispensable. Each year, some 200-300 accidents involving oil spills occur in Japanese or neighboring waters, and 10% of these accidents involve the possibility of large spills. Recent examples include the Russian tanker *Nakhodka* (13,157t), which crashed in the Sea of Japan on January 2, 1997, polluting the coastline, and the tanker *Diamond Grace* (257,000t), which ran aground in Tokyo Bay on July 2, 1997. Damage from oil spills includes direct and indirect damage to health, coastal ecosystems, commercial fishing, recreation, and shipping. Thus, an attribute-based evaluation method was adopted to estimate the damage incurred by each attribute as a result of oil spill accidents.

Following a pilot survey, a final survey was developed. The first section of this survey described the damage caused by oil spills, including damage to recreational sites, health, tidelands, and fishing ports. Several panels describing these attributes in detail were shown to respondents. The second section provided choice experiment questions regarding hypothetical oil spill accidents. Table 1 shows the attributes and levels in the survey. Standard orthogonal design was used in the choice experiments format. Figure 1 provides an example of a CE question posed in the survey. Respondents were asked to choose the one accident that they thought was most likely to occur and the one accident that they judged would result in the worst damage from three accidents. Payment was through a one-time special tax. There were eight choice set; respondents were asked iteratively eight times in CE questions.

Residents around Tokyo Bay were interviewed in person in August and September 2000. In total, 250 questionnaires were completed in the final main survey (a response rate of 42.6%). While 102 respondents were provided with probability data in the CE questions, 148 respondents were not provided with these data. We used the latter data set. For the CE format, 1184 (= 148 respondents \* 8 choice sets) samples were usable.

We compared the three models. Model 1 used only worst-choice data, and did not consider the effects of uncertainty; this is the usual CE model. Model 2 used only worst-choice data, but also considered the effects of uncertainty. This model can be estimated by (7). Model 3 was the joint estimation using worst-choice and highest probability data, and considered the effects of uncertainty. This model can be estimated by (11). We use a hundred repetitions in the simulated maximum likelihood estimation.

Table 2 shows the estimated results. ASCs are alternative specific constants. All parameters of damage attributes in the utility function were negative, except for ASCs. All parameters but ASCs of model 1 were significant at the

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<sup>\*4</sup> A scale parameter is required in usual joint estimation models on a combination of revealed preference (RP) and stated preference (SP) data, since a variance of RP is not equal to a variance of SP. In our model, variances of re-scaled expected utility and re-scaled probabilistic weight are equivalent, therefore, additional scale parameter is not required.

**Table.1: Attributes and Levels**

Attributes	Levels
Cleanup costs (one-time special tax per household)	5,000 yen 10,000 yen 30,000 yen 90,000 yen
Health effects (the number of people damaged from smell and headaches)	0 people 10000 people
Tidelands (damaged ratio of tidelands)	10 % 21 % 52 % 76 %
Fishing ports (damaged ratio of fishing ports)	0 % 34 %
Recovery period (estimated recovery period of oil spill)	2 year 4 year 8 year 16 year

1% level. In model 2, health effects and fishing ports were not significant in the utility function. This shows that it is difficult to decompose stated worst-choice data into utility and probability functions. In model 3, all parameters in the utility function and in the probability function were significant at the 1% level, except for ASCs. This result suggests that joint estimation using worst-choice and highest probability data can be decomposed into utility and probability functions.

In model 3, cleanup costs, Tidelands, and recovery period of re-scaled probabilistic weight function have negative signs. This means that there is some tradeoff between the damage of oil spill and the probability of the accident; while the probability of huge accident is low, the probability of small scale accident is high. Furthermore, a negative sign of cleanup cost shows that people may think that the probability of extremely expensive payment is not high. If the respondents thought that real payment is lower than the clean up cost of profiles, estimated willingness to pay may be higher than true value<sup>\*5</sup>. On the other hand, the health effects and fishing ports have positive sign. These two variables have only two levels; one level is no damage and other level is some damage. Positive sign means that the respondents might think that the probability of no damage was lower than some damage.

Next, we considered the estimation of the welfare from protection against the damage caused by oil spills. When the utility function is linear in the attributes, the total differential of the utility function is:

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<sup>\*5</sup> While dichotomous choice contingent valuation format is incentive compatible under some assumption, choice experiments format is not. See Carson et al. (2000).



**Table.2: Estimated Parameters**

	Variables	Model 1 Worst choice data	Model 2 Worst choice data	Model 3 Joint data
Re-scaled utility function ( $\hat{\beta}$ )	Cleanup costs (10,000 yen)	-0.1643 *** (-16.01)	-0.1916 *** (-7.09)	-0.1387 *** (-7.29)
	Health effects (10,000 person)	-0.4712 *** (-6.36)	0.1017 (1.37)	-0.1020 *** (-2.88)
	Tidelands (100 %)	-0.8762 *** (-6.32)	-0.2317 * (-1.71)	-0.4929 *** (-5.07)
	Fishing ports (100 %)	-1.6364 *** (-7.53)	-0.2510 (-1.13)	-0.4210 *** (-3.59)
	Recovery period (year)	-0.0654 *** (-9.13)	-0.0286 *** (-4.48)	-0.0413 *** (-7.01)
	ASC1	0.1975 ** (2.26)	0.1381 ** (2.09)	0.0664 (1.37)
	ASC2	0.1425 * (1.76)	0.0977 (1.57)	0.0699 (1.65)
	Re-scaled probabilistic weight function ( $\hat{\alpha}$ )	Cleanup costs (10,000 yen)		-0.0754 *** (-2.65)
Health effects (10,000 person)			0.5808 *** (4.28)	0.1216 *** (2.71)
Tidelands (100 %)			0.5735 ** (2.52)	-0.2533 *** (-2.65)
Fishing ports (100 %)			1.6511 *** (4.15)	0.5345 *** (3.12)
Recovery period (year)			0.0377 *** (2.94)	-0.0211 *** (-3.73)
Constant			1.3553 *** (3.37)	3.4558 *** (11.76)
Log-likelihood n			-986.725 1184	-923.617 1184

$$dV = \beta_M dM + \sum_k \beta_k dx_k \quad (12)$$

where  $M$  is income,  $\beta_M$  is the marginal utility of income,  $\beta_k$  is the marginal utility of the attribute  $x_k$ , and the estimated parameter utility is assumed to be held constant ( $dV=0$ ). The monetary measure for a 1-unit change in attribute  $x_k$  is

$$MWTP_k = -\frac{\beta_k}{\beta_M} = \frac{\beta_k}{\beta_C} \quad (13)$$

where  $\beta_C$  is the estimated parameter of the cleanup costs<sup>\*6</sup>.

Table 3 shows the marginal willingness-to-pay (WTP), estimated by the parameters of model 1 and 3 in Table 2<sup>\*7</sup>. The marginal WTPs of all attributes in model 1 are higher than model 3. This suggests that the marginal WTPs of the usual CE model without consideration of uncertainty may be overestimated in cases of uncertainty.

**Table.3: Estimated Marginal WTPs**

	Model 1	Model 3	Model 1/ Model 3
Health effects (yen / 100 person)	287 [195 - 386]	74 [22 - 130]	3.90
Tidelands (yen / %)	533 [371 - 720]	355 [257 - 448]	1.50
Fishing ports (yen / %)	996 [722 - 1,281]	304 [137 - 513]	3.28
Recovery period (yen / 10 year)	398 [300 - 513]	298 [239 - 371]	1.34

Note: The numbers in brackets are 95% confidential intervals which are obtained by the Monte Carlo simulation based on 1000 random draws. \$1=106 yen on August 2000.

## 4 Discussion

We extended a CE model for environmental risks using a joint model with stated worst-choice and highest probability data. Empirical results were as follows: (1) it is difficult to decompose stated worst-choice data into utility and probability functions; (2) joint estimation using worst-choice and highest probability data can be decomposed into utility and probability functions; (3) estimated WTPs in the usual CE model without consideration of uncertainty are significantly different from the ones in the joint model.

<sup>\*6</sup> Note that  $x_k$  is the attributes of accidents and  $\beta_k$  has negative sign.

<sup>\*7</sup> Since estimated parameters of Model 2 are not significant, marginal WTPs of model 2 are omitted.

These results suggest that the usual CE model may be unsuitable in cases of uncertainty, whereas the joint estimation model using stated worst-choice and highest probability data may be more effective. However, estimated WTP depends on the respondents' subjective judgment of the probable occurrence of oil spill accidents. The respondents are not experts in environmental risk, and their assessment of the likelihood of accidents occurring may be different from the actual probability. Further studies are required to estimate environmental risks.

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