The Importance of Eliminating Unrealistic Alternatives in Choice Experiments*

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Abstract

A D-efficient design, which minimizes the confidence region for parameter estimators, is often adopted in choice experiment studies. This is generally recommended to be used from the viewpoint of statistical efficiency, but it has a defect in that the choice sets commonly include some unrealistic alternatives. The purpose of this paper is to examine the issue of whether, and to what degree we should eliminate such unrealistic alternatives from the choice sets. We conduct the choice experiment survey in relation to a forest zoning plan with three types of choice designs, in which the number of the unrealistic alternatives eliminated are different, and then compare the performances of these three designs, through the estimation of random-parameters logit (RPL) models. As a result, we conclude that it is important to eliminate unrealistic alternatives in choice experiments. Also, we recommend imposing strict cost-feasible conditions on profile designs.

1 Introduction

In recent studies, a D-efficient design is often adopted when designing the profiles of choice experiments (e.g. Carlsson and Martinsson[6], Lusk, Roosen, and Fox[15], Carlsson[5]). This is the design that minimizes the determinant of a covariance matrix for parameter estimators, which is called "D-error", and is generally recommended to be used from a viewpoint of statistical efficiency (see Huber and Zwerina[10], Carlsson and Martinsson[7]). However, the procedure that minimizes D-error often generates an unrealistic combination of attributes as the alternatives. Most researchers, in choice experiment studies, do not eliminate such unrealistic alternatives from the choice sets.[1] This may cause biases and large variances of estimators in empirical studies. And yet, eliminating unrealistic alternatives often causes linearity among the independent variables and can thus lead to an inefficient estimation. Therefore, this paper will compare the estimation results of the utility functions in the designs,

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[1] We can find only a few choice experiment studies using a design with plausible alternatives, such as in Morey, Buchanan, and Waldman[17], or Blamey *et al.*[3]. Also, Maddala, Phillips, and Johnson[16] argue the necessity of reducing the respondent's cognitive burden in designing the profiles.

both with and without unrealistic alternatives, and then examine the necessity of eliminating unrealistic alternatives in choice experiments.

We have prepared three types of choice designs in the survey regarding a forest zoning plan in Kanagawa prefecture, Japan. The first is a design to minimize D-error without eliminating most other unrealistic alternatives. The second is a design to minimize D-error after eliminating some of the unrealistic alternatives. The third is the design to minimize D-error after eliminating the alternatives that do not satisfy the cost-feasible conditions described later, in addition to the alternatives that were eliminated in the second design. Thus, the closer to the third order, the fewer the unrealistic alternatives are, but the more likelihood there will be linearity among the independent variables.

The analysis procedure is as follows. First, using a random-parameters logit (RPL) model, we will test whether the coefficient parameters of each attribute are fixed among people. Although a standard multinomial logit (MNL) model is often used in conjoint studies, the MNL model requires the extremely restrictive assumption that the coefficient parameters of each attribute are fixed among people. In this analysis, we will estimate the RPL models, which allow the coefficient parameters to vary among people, and MNL models in each design, and then test whether there are significant differences between those. Also, in estimating the models, we will distinguish the attributes with random coefficient parameters from the attributes with fixed coefficient parameters and then examine how this distinction occurred.

Second, we will test whether parameters are equal for all designs. In the case when the hypothesis of the equality for a parameter is rejected, we will observe how the parameter estimate varies with the elimination of the unrealistic alternatives and then examine this tendency. Moreover, we will compare the variances of each parameter estimator among these three designs, and clarify whether the variances increase with the elimination of the unrealistic alternatives, according to theorem.

Third, we will compare the estimated willingnesses to pay (WTPs) among these three designs. We will simulate the distributions for the differences of WTPs between any two designs on the basis of the covariance matrices and then test whether the differences are significant. Finally, we will present the most desirable design of these three designs by synthesizing these analysis results.

This paper is structured as follows. Section 2 explains RPL models. Section 3 describes the outline of this survey and the profile designs. Section 4 examines the estimation results of RPL models, and then compares the parameter estimates and the variances among the three designs. Section 5 compares the estimated WTPs among the three designs. Section 6 offers the conclusion of this paper.

2 Random-Parameters Logit Model

RPL models allow the parameters to vary among people or among choice situations. Because of the flexible specification, RPL models have been widely used, as well as in recent conjoint studies (e.g. Train[21], Brownstone and Train[4], Revelt and Train[19], Layton[13], Layton and Brown[14], Goett, Hudson, and Train[8], West *et al.*[23], Kuriyama *et al.*[12]). In this section, we explain the structure of RPL models.

Suppose that each respondent meets a choice among J alternatives in T choice situations. Then, the utility U_{ijt} that the respondent i obtains from the alternative j in the choice situation t is represented by

$$U_{ijt} = \beta_i' x_{ijt} + \varepsilon_{ijt}, \tag{2.1}$$

where x_{ijt} is the attribute vector of the alternative j that the respondent i meets in the choice situation t, β_i is the coefficient vector of x_{ijt}, and ε_{ijt} is the stochastic error term which follows i.i.d. extreme value distribution. The respondent i chooses the alternative k in the choice situation t when $U_{ikt} > U_{ijt}$, $\forall k \neq j$. Here, let y_{it} denote the alternative that the respondent i chooses in the choice situation t. Then, the probability conditional on β_i that the respondent i chooses y_{it} in the choice situation t is represented by the following equation (see McFadden[18]).

$$L(y_{it}|\beta_i) = \frac{\exp(\beta_i' x_{iy_{it}t})}{\sum_j \exp(\beta_i' x_{ijt})}. \tag{2.2}$$

Also, since ε_{ijt} is assumed to be independently distributed over choice situations, the conditional probability of a sequence of choices for the respondent i is represented by

$$P(y_i|\beta_i) = \prod_t L(y_{it}|\beta_i), \tag{2.3}$$

where $y_i := (y_{i1}, \cdots, y_{iT})$.

If β_i is fixed among people, the probability of equation (2.3) is not conditional, and therefore it is a standard MNL model. However, this assumption means that the partial utilities obtained from an attribute level are equal for all people, and this is extremely restrictive. To relax this restriction, we can specify the coefficient parameter vector as random variable vector β which follows the density function $g(\beta|\theta)$, where θ is the parameter vector of this density function.[2] This is a RPL model.[3] The unconditional probability is obtained by the integral of equation (2.3) with respect to β.

$$P(y_i|\theta) = \int P(y_i|\beta)g(\beta|\theta)d\beta. \tag{2.4}$$

Although the likelihood function is theoretically constructed on the basis of the choice probabilities represented by equation (2.4), in practice, we can not apply the maximum likelihood method strictly, since the integral in equation (2.4) does not have a closed form in general. Thus, we approximate the integral through a simulation in accordance with many previous studies. The procedure of this approximated calculation is as follows. First, we draw β from the density g R times. Second, we insert each drawn β into the equation (2.3) and obtain R probabilities. Finally, we calculate the average of R probabilities and use it as the approximation of equation (2.4). Let $\beta^{r|\theta}$ denote the r^{th} drawn β. The simulated probability

[2]In this paper, we specify so that β varies among people, but does not vary among choice situations.

[3]RPL models are also called mixed logit models, since the choice probability is represented by the mixture of a logistic probability with a density as shown in equation (2.2) and (2.3). As for the recent specifications and the applications in mixed logit models, see Brownstone and Train[4].

is represented by

$$\tilde{P}(y_i|\theta) = \frac{1}{R}\sum_r P(y_i|\beta^{r|\theta}). \tag{2.5}$$

We can construct the following simulated log-likelihood function on the basis of these simulated probabilities, and estimate θ to maximize this function.

$$SLL = \sum_i \ln \tilde{P}(y_i|\theta). \tag{2.6}$$

3 Choice Experiment Design

3.1 Survey Outline

We conducted the main survey in October 2001 through two pilot surveys in 2000-2001. The survey population was the inhabitants of Kanagawa prefecture. We randomly drew 2200 respondents from a phone directory, and then sent the questionnaire to them through the mail along with a small gift, a sink-corner strainer made from kenaf. The number of valid responses was 798, with a response rate of 36.3%.

3.2 Attributes and Levels in Profiles

The Kanagawa prefecture government manages the forest by categorizing them into three zones and two areas. As shown in Figure 1, the forest is categorized by altitude into the Ecosystem Conservation Zone (ECZ), the Timber Production Zone (TPZ) and the Landscape Conservation Zone (LCZ). Parts of the forest are also assigned to the Water Source Conservation Area (WSA) and the Rest and Recreation Area (RRA), which overlap with the three zones. We make up the profiles by combining six attributes, namely five proportions of each district to the total forest area and a one-time payment for the zoning. Below, for simplicity, we denote the proportions of each district by "P-"s, such as P-ECZ, P-TPZ, and P-WSA.

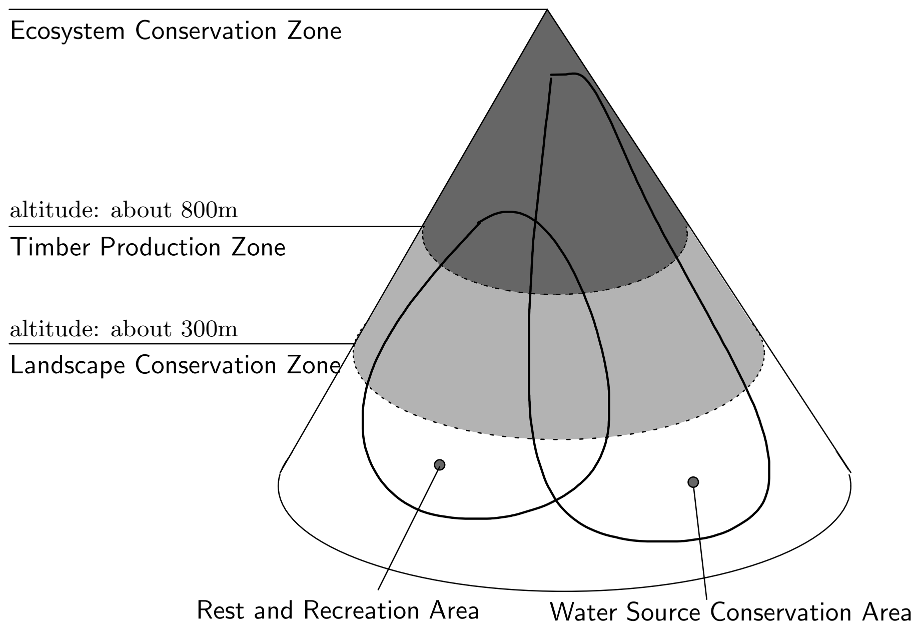

Figure 1: Image of Forest Zoning

The levels of the attributes are shown in Table 1. As for levels of the five proportions, we set the level larger than the status quo as level 1 or level 2, and the level smaller than the status quo as level 3 or level 4. As for the levels of the payment, since the level set chosen empirically demonstrated a good performance in the pilot surveys, we also adopt it in the main survey .

Table 1: Attributes and Levels

Attributes	Level 1	Level 2	Level 3	Level 4	Level 5	status quo
P-ECZ	50%	30%	20%	0%	-	21%
P-TPZ	70%	50%	30%	10%	-	47%
P-LCZ[a]	-	-	-	-	-	32%
P-WSA	90%	70%	50%	20%	-	52%
P-RRA	40%	30%	20%	0%	-	21%
Payment	20,000 yen	10,000 yen	5,000 yen	2,000 yen	500 yen	0 yen

[a] P-LCZ is automatically settled from the restriction that the sum of three zone percentages is 100.

Before we start the conjoint questions, we gave respondents the following descriptions of each district and Figure 1.

Ecosystem Conservation Zone (ECZ) A forest ecosystem is composed of various living things, such as mammals, birds, insects, and plants. In this zone, the forest is managed to conserve such a natural ecosystem.

Timber Production Zone (TPZ) In this zone, the forest is managed for the purpose of timber production. The timber is improved by appropriate forest management, and the product is supplied constantly.

Landscape Conservation Zone (LCZ) Flatland forests near urban areas play an important role in the urban landscape and buffer our lives from wind, noise and so on. In our daily life, they may provide rest and, in times of disaster, refuge. In this zone, the forest is managed to keep such a comfortable living environment.

Water Source Conservation Area (WSA) In this area, the forest is managed to obtain good water stably. Now 52% of the total forest area in Kanagawa prefecture is assigned to this area.

Rest and Recreation Area (RRA) In this area, the forest is managed to enable urban people to enjoy recreational activities there. Now 21% of the total forest area in Kanagawa prefecture is assigned to this area.

Table 2 shows an example of the conjoint questions. We ask each respondent to choose the best plan of the four different forest zoning plans, which include the status quo. Also, we repeat such a conjoint question 8 times for each respondent, each time changing the combination of the levels.

Conjoint Question

Suppose that the following forest zoning plans are prepared in Kanagawa prefecture.

In Plan 1, 0% of the total forest area in Kanagawa prefecture is assigned to the Ecosystem Conservation Zone, 30% of the total forest area is assigned to the Landscape Conservation Zone, and the remaining 70% is assigned to the Timber Production Zone. In addition, 30% of the total forest area is assigned to the Water Source Conservation Area, and 10% of the total forest area is assigned to the Rest and Recreation Area. In this case, your household needs to pay 5,000 yen.

Likewise, your household needs to pay 2,000 yen to realize Plan 2, and 10,000 yen to realize Plan 3.

Plan 4 is the status quo. Now, the Ecosystem Conservation Zone occupies 21% of the total forest area, the Landscape Conservation Zone occupies 32% of the total forest area, the Timber Production Zone occupies 47% of the total forest area, the Water Source Conservation Area occupies 52% of the total forest area, and the Rest and Recreation Area occupies 21% of the total forest area.

Forest Zoning Plans

	Plan 1	Plan 2	Plan 3	Plan 4
Ecosystem Conservation Zone	0%	20%	40%	21%
Landscape Conservation Zone	30%	10%	30%	32%
Timber Production Zone	70%	70%	30%	47%
Water Source Conservation Area	30%	20%	70%	52%
Rest and Recreation Area	10%	0%	40%	21%
Payment	5,000 yen	2,000 yen	10,000 yen	0 yen
	↓	↓	↓	↓
Which is the best plan for you?	1	2	3	4

Below, we show such a set of plans. Please choose the best plan for you from the 4 zoning plans. The payment is one-time. The collected funds are used only for the forest zoning in Kanagawa prefecture. Note that your available money decreases by this payment.

Figure 2: Conjoint Question

3.3 Profile Designs

This study tackles the problem of whether and to what degree we should eliminate unrealistic alternatives in choice experiment surveys. From this viewpoint, we prepare the three types of choice designs in this survey. The first is the design to minimize D-error without eliminating most of the unrealistic alternatives, denoted V_1. In this design, we only eliminate the alternatives with the combination of P-ECZ, 50%, and P-TPZ, 70%, since the sum of those is over 100%. The estimation in this design V_1 is theoretically expected to be efficient.

The second is the design to minimize D-error after eliminating some of the unrealistic alternatives in advance, denoted V_2. Concretely, we eliminate the alternatives with the combination shown in Table 2, in addition to the alternatives eliminated in V_1. Although the unrestricted D-efficient design is theoretically efficient design, it commonly includes some unrealistic combinations of the attributes. From this analysis, we can see how differences are produced for the mean and the variance of estimators, between the designs with and without unrealistic alternatives.

Table 2: Combination of the Attributes Excluded in V_2

Combination	Reason for Excluding
P-ECZ : Level 1 P-RRA : Level 1	The combination of the maximum levels of P-ECZ and P-RRA is unrealistic, since the forest is conserved in ECZ, but is partially developed in RRA.
P-TPZ : Level 1 P-RRA : Level 1	The combination of the maximum levels of P-TPZ and P-RRA is unrealistic, since, while the forest is partially developed both in TPZ and in RRA, the purposes of the developments are different.
P-WSA : Level 1 P-RRA : Level 1	The combination of the maximum levels of P-WSA and P-RRA is unrealistic, since the forest is conserved in WSA, but is partially developed in RRA.
P-WSA : Level 1 P-TPZ : Level 1	The combination of the maximum levels of P-WSA and P-TPZ is unrealistic, since the forest is conserved in WSA, but is partially developed in TPZ.
Payment : Level 5 P-RRA : Level 1	The combination of the minimum level of Payment and the maximum level of P-RRA is unrealistic, since, if RRA is assigned at the maximum level, we need to pay much more for the development.
Payment : Level 1 P-RRA : Level 4	The combination of the maximum level of Payment and the minimum level of P-RRA is unrealistic, since, if RRA is assigned at the minimum level, we do not need to pay very much for the development.

The third is the design to minimize D-error after eliminating the alternatives that do not satisfy the cost-feasible conditions, shown in Table 3, in addition to the alternatives eliminated in V_2, denoted V_3. These conditions impose a restriction so that the combination of the payment and the total proportion of the forest conservation districts, which include ECZ, LCZ, WSA and RRA, is feasible. As described above, the larger that the number of the subscript is, the fewer unrealistic alternatives there are, but the more likely an inefficient estimation will be reached. By comparing the result in V_2 with that in V_3, we can determine whether unrealistic alternatives should be strictly eliminated.

Table 3: Cost-feasible Conditions

Total Proportion of Conservation Districts[a]	Payment
80-118%	500 yen
118-156%	2,000 yen
156-194%	5,000 yen
194-232%	10,000 yen
232-270%	20,000 yen

[a] This means the sum of P-ECZ, P-LCZ, P-WSA and P-RRA.

4 Results

4.1 Estimation Results of RPL Models

In this analysis, we pick up P-ECZ, P-LCZ, P-WSA, P-RRA and payment as the variables included in the utility function and then specify the main effect models. The reason for eliminating P-TPZ from the models is because if we include P-TPZ in the models, then the coefficient parameters are not identified by the strict linearity among the variables. Moreover, we assume that the respondents do not obtain the utility from TPZ, and thus eliminate the P-TPZ from the utility function completely. By this assumption, the marginal utilities from ECZ and LCZ are identified.[4] Also, we set an alternative-specific constant (ASC), which is the dummy variable that equals 1 when the status quo (Plan 4) is chosen, as the model, and examine whether there is the status quo bias.[5] If the sign of ASC is positive, there is a status quo bias in the response.

In RPL models, we assume that each coefficient parameter follows the normal distribution, and we draw 300 parameters on the basis of Halton sequences to calculate the simulated probability represented by equation (2.5).[6] Since we can not see whether each coefficient

[4]Without this assumption, the estimated coefficients of P-ECZ and P-LCZ are the true coefficients of them minus the coefficients of P-TPZ. For example, suppose that the utility function U is specified as $U = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$, subject to $x_1 + x_2 + x_3 = 1$. This equation is developed as follows.

$$\begin{aligned} U &= \beta_1 x_1 + \beta_2 x_2 + \beta_3 (1 - x_1 - x_2), \\ &= \beta_3 + (\beta_1 - \beta_3) x_1 + (\beta_2 - \beta_3) x_2. \end{aligned}$$

Since the constant term represented by β_3 is not identified in logit models, here the coefficients of x_1 and x_2, namely $\beta_1 - \beta_3$ and $\beta_2 - \beta_3$, are only estimated. If we assume that $\beta_3 = 0$, then β_1 and β_2 are identified.

[5]As for the status quo bias, see Samuelson and Zeckhauser[20] and Adamowicz *et al.*[1]

[6]A Halton sequence is a simulated random sequence, which is derived on the basis of prime numbers, developed by Halton[9]. As shown by Bhat[2] and Train[22], the necessary number of draws on Halton sequences to estimate parameters at a given confidence level is smaller than that on random sequences.

parameter is a random parameter in advance, we assume that all the coefficient parameters are random parameters, and treat the coefficients so that the standard deviation parameters are not significant as fixed parameters. Finally, we select the models with the minimum AIC. The estimation results of RPL models and MNL models for each design are shown in Table 4.[7]

[7] To estimate the models, we use GAUSS 4.0 that is the product of Aptech Systems, Inc.

Table 4: Estimation Results of RPL Models and MNL Models

Variable	Design V_1					Design V_2					Design V_3				
	RPL Model			MNL Model		RPL Model			MNL Model		RPL Model			MNL Model	
	Coefficient		S.E.	Coefficient	S.E.	Coefficient		S.E.	Coefficient	S.E.	Coefficient		S.E.	Coefficient	S.E.
Mean															
P-ECZ	0.0673	(R)[a]	0.0058	0.0393	0.0030	0.0607	(R)	0.0056	0.0408	0.0037	0.0825	(R)	0.0074	0.0409	0.0036
P-LCZ	0.0251	(R)	0.0033	0.0168	0.0019	0.0264	(R)	0.0032	0.0207	0.0022	0.0363	(R)	0.0051	0.0165	0.0028
P-WSA	0.0175	(R)	0.0025	0.0108	0.0013	0.0226	(R)	0.0022	0.0153	0.0013	0.0351	(R)	0.0050	0.0123	0.0026
P-RRA	0.0169	(R)	0.0035	0.0084	0.0021	0.0203	(F)	0.0038	0.0139	0.0026	0.0332	(F)	0.0051	0.0144	0.0030
Payment	−0.1033	(R)	0.0153	−0.0410	0.0057	−0.1426	(R)	0.0176	−0.0613	0.0062	−0.4503	(R)	0.0730	−0.0900	0.0290
ASC[b]	1.6540	(R)	0.3103	1.1386	0.1297	-	(R)	-	0.9360	0.1289	-	(R)	-	1.0309	0.1428
Standard Deviation															
P-ECZ	0.0425		0.0043			0.0438		0.0061			0.0439		0.0057		
P-LCZ	0.0228		0.0032			0.0282		0.0036			0.0279		0.0035		
P-WSA	0.0192		0.0027			0.0199		0.0028			0.0289		0.0046		
P-RRA	0.0230		0.0049			-		-			-		-		
Payment	0.1375		0.0149			0.1401		0.0201			0.4681		0.0803		
ASC	5.1194		0.4922			4.3985		0.3304			6.1074		0.5591		
Sample Size	2096			2096		1893			1893		2020			2020	
Log-likelihood	−1714.18			−2509.44		−1638.55			−2251.02		−1635.23			−2512.72	
AIC	3452.35			5030.88		3301.10			4514.04		3294.47			5037.43	
McFadden's Pseudo R^2	0.4101			0.1364		0.3756			0.1422		0.4161			0.1027	
Cragg & Uhler's Pseudo R^2	0.7245			0.3358		0.6902			0.3476		0.7301			0.2643	

[a] We denote a fixed parameter as "F", and a random parameter as "R".

[b] ASC is a dummy variable that equals 1 when the status quo (Plan 4) is chosen, and equals 0 when the status quo is not chosen.

We can see from this table that the AICs of RPL models are much smaller than those of the MNL models, and the pseud-R^2s of the RPL models are much larger than those of the MNL models in all of the designs. These results demonstrate that RPL models are superior to MNL models.

Consider in detail the implications of the estimation results. First, the signs of the mean parameter estimates for all forest conservation districts are positive in all designs, and the signs of the mean parameter estimates for payment are negative in all designs. This result means that the larger the forest conservation districts are, the larger the respondents' utilities are, and that the larger the payment is, the smaller the respondents' utilities are. The signs of all the mean parameter estimates seem to have a logical consistency. Second, the mean parameter estimates for each district are arranged in order of size as ECZ, LCZ, WSA and RRA in all designs. This result suggests that three samples are homogeneous among the designs. Third, the coefficients of P-ECZ, P-LCZ and P-WSA are treated as random parameters in all of the designs, while the coefficients of P-RRA are treated as fixed parameters in V_2 and V_3. This result means that the marginal utilities obtained from ECZ, LCZ and WSA vary among people, while the marginal utilities obtained from RRA are fixed among people in V_2 and V_3 at least. How did this difference occur? When considered from the viewpoint of economic value, the values obtained from ecosystem conservation, landscape conservation, and water source conservation seems to generally involve non-use values, such as a bequest value and an existence value, while most of the values obtained from forest recreation seems to be for an indirect use value. We conjecture that this difference is caused by the heterogeneity of non-use values among people. Fourth, the coefficients of payment are treated as random parameters in all designs. This seems to be caused by the variations of the respondents' income levels and jobs. Fifth, although the constant parameters of ASC are treated as random parameters in all designs, only the mean parameter estimate in V_1 has a positive sign, and the mean parameter estimates in V_2 and V_3 have no significant difference from 0. This result demonstrates that we can avoid the status quo bias by eliminating the unrealistic alternatives.

4.2 Testing the Equality of Parameters

In this subsection, we test whether parameters are equal among the designs, by using a likelihood ratio test.[8] In this analysis, we assume that the fewer the unrealistic alternatives are, the more precisely the respondents recognize their utility functions, and in the case that a parameter is heterogeneous between the designs, both with and without unrealistic alternatives, we interpret the difference of the parameter as a bias caused by the unrealistic alternatives. We clarify not only whether the unrealistic alternatives cause the biases of parameter estimators by testing the equality of each parameter among V_1, V_2 and V_3, but also at which stage the biases are caused by testing the equality of each parameter between V_1 and V_2, and also between V_2 and V_3. The results of likelihood ratio tests are shown in Table 5.

Table 5: Likelihood Ratio Test Results for the Equality of Each Parameter

Coefficient	Type[a]			V_1, V_2 and V_3		V_1 and V_2		V_2 and V_3	
	V_1	V_2	V_3	LR statistic	p-value	LR statistic	p-value	LR statistic	p-value
Mean									
P-ECZ	R	R	R	7.5074	0.0234	0.8727	0.3502	7.2869	0.0069
P-LCZ	R	R	R	5.0920	0.0784	0.1138	0.7359	3.5496	0.0596
P-WSA	R	R	R	12.5162	0.0019	2.5976	0.1070	6.2737	0.0123
P-RRA	R	F	F	8.4186	0.0149	0.5193	0.4711	4.8166	0.0282
Payment	R	R	R	35.1637	0.0000	4.0284	0.0447	25.8434	0.0000
Standard Deviation									
P-ECZ				0.0543	0.9732	0.0378	0.8458	0.0002	0.9886
P-LCZ				1.9355	0.3799	1.5034	0.2201	0.0031	0.9560
P-WSA				5.3624	0.0685	0.0320	0.8579	3.7190	0.0538
Payment				38.6806	0.0000	0.0142	0.9051	34.9378	0.0000
ASC				6.7846	0.0336	1.5763	0.2093	6.6929	0.0097

[a] We denote a fixed parameter as "F", a random parameter as "R".

As a beginning, consider the implication of the result for the mean parameters. We see from Table 5 that the hypothesises of the equality among the three designs are rejected at 5% significant level for all the mean parameters, except for that of P-LCZ. This result shows

[8]Here, the unrestricted models are the three RPL models shown in Table 4, and the restricted models are the models assumed that a parameter is equal among the designs. If an unrestricted log-likelihood is denoted by $\ln L(\hat{\theta})$, and a restricted log-likelihood is denoted by $\ln L(\hat{\theta_r})$, then a likelihood ratio test statistic is represented by $-2[\ln L(\hat{\theta_r}) - \ln L(\hat{\theta})]$, which follows a χ^2 distribution with k degrees of freedom, where k is the number of restrictions imposed.

that unrealistic alternatives cause the biases of the mean parameter estimators. Also, while the hypothesises of the equality between V_1 and V_2 are not rejected at 5% significant level for all the mean parameters, except for that of payment, the hypothesises of the equality between V_2 and V_3 are rejected at 5% significant level for all the mean parameters, except for that of P-LCZ, whose p-value is also only about 0.06. From this result, we can suggest that in order to avoid the bias caused by the unrealistic alternatives we need to impose the strict cost-feasible conditions in V_3 on profile designs.

In addition, comparing the mean parameter estimates in V_2 with those in V_3 (Table 4), we can see that the mean parameter estimates in V_3 are larger than those in V_2. This means that the fewer unrealistic alternatives there are, the more strongly the respondents understand the utilities obtained from the forest multifunctionality and the utilities lost by the payment, and this seems to support the assumption described above, "the fewer the unrealistic alternatives are, the more precisely the respondents recognize their utility functions".

Next, consider the implication of the result for the standard deviation (SD) parameters. We see from Table 5 that the hypothesises of the equality among the three designs are rejected at 5% significant level for the SD parameters of payment and ASC. As the consideration for the mean parameters, from the test results for the equality between V_1 and V_2, and also between V_2 and V_3, we see that the heterogeneity of these SD parameters reflects the heterogeneity of those between V_2 and V_3.

Comparing the SD parameter estimates in V_2 with those in V_3 (Table 4), as for either SD parameter estimate of payment and ASC, we can see the trend that the fewer the unrealistic alternatives are, the larger the SD parameter estimate is. This means that the distributions of the respondents' utilities that are lost by the payment and the additional utilities that are obtained from the status quo choice are centralized, when the respondents meet more unrealistic alternatives. This phenomenon is interpreted as follows. First, notice the SD parameter of payment. Here, the unrealistic alternatives mean the alternatives in which the payment is too small for the more costly plan or in which the payment is too large for the less costly plan. The respondents who meet the former may feel better about the smaller payment, and they may choose this alternative, which should not be chosen theoretically, because of the underestimate of the utilities lost by the payment. And the people who behave in this manner seem to have relatively large negative utilities for the payment, since it is unlikely that the respondents who have small negative utilities for the payment will change their choices, even if they underestimate the utilities lost by the payment. On the other hand, the respondents who meet the latter may feel worse about the large payment, and may not choose this alternative, which should be chosen theoretically, because of the overestimate of the utilities lost by the payment. And the people who behave in this manner seem to have relatively small negative utilities for the payment. As a result, the variance of the utilities lost by the payment is smaller in V_2, which has some unrealistic alternatives.

Second, notice the SD parameter of ASC. Similarly, the respondents, who meet the alternatives in which the payment is too small for the more costly plan, may choose this alternative, which should not be chosen theoretically, because of the underestimate of the additional utilities obtained from the status quo choice. And the people who behave in this manner seem to have relatively large utilities for the status quo, since it is unlikely that the respondents who have smaller utilities for the status quo will change their choices, even if they underestimate the additional utilities obtained from the status quo choice. On the other hand, the respondents, who meet the alternatives in which the payment is too large for the less costly plan, may choose the status quo, which should not be chosen theoretically, because of the overestimate of the additional utilities obtained from the status quo choice. And the people who behave in this manner seem to have relatively small utilities for the status quo. This is a kind of protest response for unrealistic scenarios. As a result, the variance of the additional utilities obtained from the status quo is smaller in V_2, which has some unrealistic alternatives.

4.3 Comparing the Variances of Estimators

In this subsection, we compare the variances of each parameter estimator among the designs. Table 6 shows the standard errors of each estimator and the determinants of the covariance matrices for the estimator vectors.

Table 6: Standard Errors, Coefficients of Variation and Determinants of Covariance Matrices

Coefficient	Standard Error$\times\sqrt{N}^a$			Coefficient of Variation$\times\sqrt{N}^b$		
	V_1	V_2	V_3	V_1	V_2	V_3
Mean						
P-ECZ	0.2658	0.2442 *	0.3309	3.9484 †	4.0247	4.0114
P-LCZ	0.1493	0.1413 *	0.2278	5.9536	5.3527 †	6.2707
P-WSA	0.1123	0.0957 *	0.2256	6.4024	4.2392 †	6.4319
P-RRA	0.1623	0.1647	0.2278	9.6035	8.0950	6.8693 †
Payment	0.6985 *	0.7663	3.2826	6.7608	5.3729 †	7.2904
ASC	14.2084			8.5902		
Standard Deviation						
P-ECZ	0.1985 *	0.2647	0.2576	4.6702 †	6.0383	5.8620
P-LCZ	0.1470 *	0.1548	0.1579	6.4332	5.4931 †	5.6520
P-WSA	0.1221 *	0.1223	0.2077	6.3456	6.1375 †	7.1887
P-RRA	0.2241	0.3391		9.7390	18.9861	18.0292
Payment	0.6815 *	0.8767	3.6096	4.9573 †	6.2565	7.7110
ASC	22.5337	14.3769 *	25.1275	4.4016	3.2686 †	4.1143
Determinant	0.1662	0.0913	0.2372	30.5622	20.8922	21.6124

[a] "N" means a sample size.

[b] Here, coefficients of variation are calculated by dividing standard errors by point estimates, namely inverses of t-values.

[c] We mark the minimum of the three standard errors with "*", and the minimum of the three coefficients of variation with "†" for each parameter.

Since each component of a covariance matrix is inversely proportional to the sample size N, to compare among the designs, we multiply the standard errors by $\sqrt{N}$ in Table 6. Also, since the determinant of a covariance matrix depends on the number of parameters, namely the order of a covariance matrix k, as well as the sample size N, we multiply the determinants by N^k, and take the k^{th} root of the multiplied value in Table 6.

In Table 6, "*" means that the marked standard error is the minimum of those in the three designs for each parameter. We see from this table that, although the design which has the most "*"s is V_1, the design which has the minimum determinant is V_2, and therefore, from the viewpoint of minimizing a confidence region, the estimation in V_2 is more efficient than that in V_1. This result demonstrates that the theoretically efficient designs are not necessarily efficient in practice, and therefore suggests that the respondents who meet the unrealistic alternatives respond on the basis of the utilities with large errors.

Also, in this analysis, we take into consideration that a variance depends on the mean in general, and thus we compare the coefficients of variation, which are calculated by dividing standard errors by point estimates, namely the inverses of t-values, among the three designs.[9] In Table 6, "†" means that the marked coefficient of variation is the minimum of those in the three designs for each parameter. We see from this table that V_2 does not have only the most "†"s, but it also has the minimum determinant, and that the determinant in V_3 bears comparison with that in V_2. From these results, we can conclude that, from the viewpoint of minimizing a confidence region, eliminating the unrealistic alternatives is important when designing conjoint profiles.

5 Comparing the WTP Estimators

Finally, we compare the WTPs for each district among the three designs. Here, let β_c denote the mean parameter for payment, and let β_e denote the mean parameter for the proportion of a district. Under the specification of linear utility functions, the marginal WTPs (MWTPs) for the 1 % increase of each district are represented by $-\beta_e/\beta_c$. The point estimates and the 95% confidence intervals of MWTPs in each design are shown in Table 7.

[9]The determinants are calculated by the covariance matrices,

$$\begin{pmatrix} \frac{s_{11}}{b_1^2} & \frac{s_{12}}{b_1 b_2} & \cdots & \frac{s_{1k}}{b_1 b_k} \\ \frac{s_{21}}{b_2 b_1} & \frac{s_{22}}{b_2^2} & \cdots & \frac{s_{2k}}{b_2 b_k} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{s_{k1}}{b_k b_1} & \frac{s_{k2}}{b_k b_2} & \cdots & \frac{s_{kk}}{b_k^2} \end{pmatrix},$$

where b_i is the i^{th} parameter estimates, and s_{ij} is the (i,j) component of the covariance matrix.

Table 7: MWTPs in Three Designs (yen)

	V_1	V_2	V_3
ECZ	651.62	425.39	183.23
	[505.72 - 873.68][a]	[337.17 - 546.50]	[149.18 - 238.43]
LCZ	242.75	185.09	80.70
	[177.05 - 340.22]	[136.77 - 249.77]	[66.75 - 99.44]
WSA	169.77	158.36	77.89
	[122.00 - 239.65]	[124.67 - 205.07]	[65.51 - 94.55]
RRA	163.60	142.63	73.66
	[101.96 - 245.29]	[96.18 - 199.87]	[57.91 - 94.08]

[a] The values in square brackets are 95% confidence intervals, which are calculated by the Monte Carlo simulation with 10,000 random draws, according to the method of Krinsky and Robb[11].

We see from Table 7 that, in all of the designs, the MWTPs are arranged in order of size as ECZ, LCZ, WSA and RRA, and that the MWTP for ECZ is over twice that of the MWTP for LCZ. This result shows the respondents' large support for the conservation of the forest ecosystem.

Also, the MWTPs for each district seem to have obviously differences among the designs. Especially between the MWTPs in V_2 and in V_3, as described in Section 4, since the mean parameter estimates are obviously different, the MWTPs are also different. To clarify this, we test whether the MWTPs for each district are equal among the designs using the following procedure. First, we derive the distribution for the difference between the MWTPs in V_1 and in V_2, and that between the MWTPs in V_2 and in V_3 by the Monte Carlo simulation with 10,000 random draws, according to the method of Krinsky and Robb[11], and then construct the 95% confidence intervals. Second, by using the duality between confidence intervals and hypothesis tests, if 0 is not included in the 95% confidence interval, we reject the hypothesis that there is no difference between the two MWTPs at 5% significant level. The 95% confidence intervals are shown in Table 8.

Table 8: 95% Confidence Intervals for the Differences of MWTPs

	$\hat{MWTP_1} - \hat{MWTP_2}$	$\hat{MWTP_2} - \hat{MWTP_3}$
ECZ	[35.29 - 471.60]	[139.95 - 363.76]
LCZ	[-35.18 - 166.46]	[52.09 - 169.71]
WSA	[-54.38 - 88.13]	[42.54 - 128.05]
RRA	[-61.78 - 116.00]	[18.33 - 126.44]

[a] $\hat{MWTP_i}$ means the MWTP estimated in the design V_i for $i = 1, 2, 3$.

We see from Table 8 that, although the difference of the MWTPs between V_1 and V_2 is significant only for ECZ, the difference of the MWTPs between V_2 and V_3 is significant for all of the districts. From this result, assuming that "the fewer the unrealistic alternatives are, the more precisely the respondents recognize their utility functions", we can conclude that it is important to impose the strict cost-feasible conditions in V_3 onto the profile designs.

6 Conclusions

In this study, we conduct a choice experiment survey about the forest zoning plan using three types of choice designs, in which the number of the unrealistic alternatives that are eliminated are different, and then clarify the issue of whether and to what degree we should eliminate unrealistic alternatives in choice experiment surveys, through the estimation of RPL models. The important findings of this study are the following three points.

- We can avoid the status quo bias by eliminating unrealistic alternatives.
- We can avoid the biases of parameters included in utility functions and the biases of WTPs by eliminating unrealistic alternatives.
- We can diminish the confidence region of parameter estimators by eliminating unrealistic alternatives.

From these findings, we can conclude that it is important to minimize D-error after the elimination of the unrealistic alternatives in choice experiment designs. On the other hand, as for the problem of to what degree we should eliminate unrealistic alternatives, we respect the results in which the significant differences between the parameters in V_2 and in V_3 are confirmed, and then recommend imposing the strict cost-feasible conditions in V_3 on profile designs.

However, we have to note that this conclusion depends on the assumption that "the fewer the unrealistic alternatives are, the more precisely the respondents recognize their utility functions". The future direction of this study will be to further examine the validity of this assumption.

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