진술선호기법을 이용한 공공재 가치평가법

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Contents

I. Welfare Measurement
Utility Maximization

$$\mathbf{u = u(x, q) \ s.t., \ px + rq = m}$$

x=market goods, r = price of q

- Conditional demands for the marketed goods: $x_i = x_i(p, m\text{-}rq, q)$
- Conditional indirect utility function: $v = v(p, m\text{-}rq, q)$
- Conditional expenditure function on market goods: $e^* = m\text{-}rq = e^*(p, q, u)$
- Restricted expenditure function (= total expenditure): $e = e(p, r, q, u) = e^* + rq$
- The marginal value of a change in q: $W_q = -\frac{\partial e}{\partial q} = -\frac{\partial e^*}{\partial q} - r$
- Non-marginal changes ($q^0 \rightarrow q^1$): we use the following CS or ES

I. Welfare Measurement

Utility Maximization

CS (compensating surplus)	**ES(equivalent surplus)**
$v(p, m\text{-}rq^0, q^0) = v(p, m\text{-}rq^1\text{-}CS, q^1)$ $CS = e(p,r,q^0,u^0) - e(p,r,q^1,u^0) = -\int_{q^0}^{q^1} \frac{\partial e(p,r,q,U^0)}{\partial q} dq$	$v(p, m\text{-}rq^0\text{+}ES, q^0) = v(p, m\text{-}rq^1, q^1)$ $ES = e(p,r,q^0,u^1) - e(p,r,q^1,u^1) = -\int_{q^0}^{q^1} \frac{\partial e(p,r,q,U^1)}{\partial q} dq$
For the case of public good improvements: CS = WTP, ES = WTA	

- How big is the difference? Randall and Stoll (1980), Hanemann (1991): $\frac{CS - \Delta S}{\Delta S} \approx \frac{\Delta S}{M^0} \frac{\varepsilon}{2}$

$$\varepsilon = \frac{\partial b^*(p,q,m)}{\partial m} \frac{m}{b^*} = \frac{\eta}{\sigma}$$

ε=the price flexibility of income

η=income elasticity

σ=Allen-Uzawa elasticity of substitution between q and X

I. Welfare Measurement

Composition of the Benefits

1) Without Uncertainty

Total value = use value + existence (or nonuse) value

2) With Uncertainty

Total value = use value + existence (or nonuse) value + option value + quasi-option value

An Overview of the Valuation Methods

Revealed preference methods	Recreation demand models · travel cost method (single site demand estimation) · random utility model (site choice model) Averting behavior models Cost of illness models Hedonic price methods Hedonic wage methods
Stated preference methods	Contingent valuation methods (CVM) Contingent ranking methods (CRM) Conjoint analysis Choice experiments (CE) Contingent activity methods
Simulated market methods	Experimental auctions

I. Welfare Measurement

Advantages of SP Methods

1) RP is hopeless when X and q are separable
2) Possible to incorporates existence values (cf., weak complementarity, weak substitutability)

그림 15-4 약보완성을 이용한 환경질 개선의 편익 추정

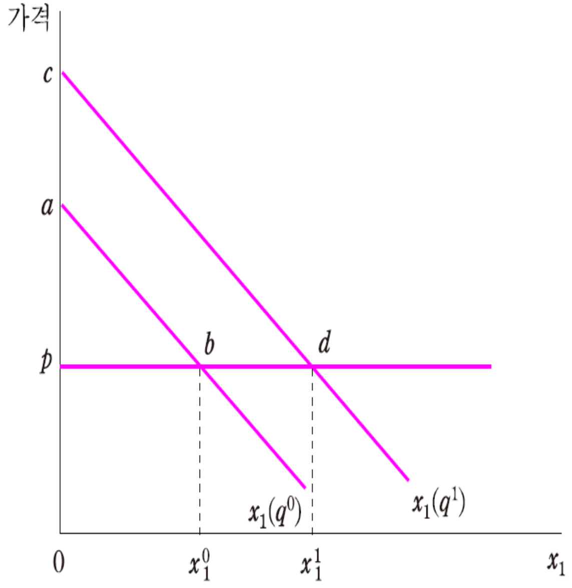
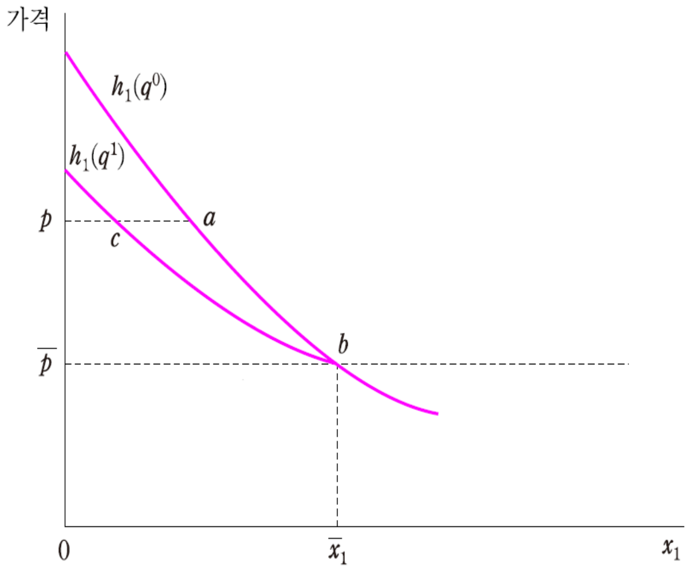


그림 15-6 약대체성을 이용한 환경질 개선의 편익 추정



II. Contingent Valuation: Basic Model
Introduction

Types of Survey Questions

1) Open Ended CV.
2) Bidding Game.
3) Payment Cards.
4) Dichotomous or Discrete Choice CV: A CV question format in which respondents are asked simple yes or no questions of the stylized form: “Would you be willing to pay $t?”

Biases of CVM Studies

1) Strategic Bias
2) Starting Point Bias (incentive compatibility)
3) Hypothetical Bias (consequentiality, Carson and Groves, 2007)
4) Embedding

II. Contingent Valuation: Basic Model

CV-RUM

With a Linear Utility Function

$$v_j(y_j, z_j) = \alpha_i z_j + \beta(y_j - t_j), i = 0,1$$

The change in deterministic utility is

$$v_{1j} - v_{0j} = (\alpha_1 - \alpha_0)z_j + \beta(y_j - t_j) - \beta y_j = \alpha z_j - \beta t_j, \alpha = \alpha_1 - \alpha_0$$

Therefore,

$$\Pr(yes_j) = \Pr[\alpha z_j - \beta t_j + \varepsilon_j > 0] = \Pr[-(\alpha z_j - \beta t_j) < \varepsilon_j]$$
$$= 1 - \Pr[-(\alpha z_j - \beta t_j) > \varepsilon_j] = \Pr[\varepsilon_j < \alpha z_j - \beta t_j]$$

Probit Assumption

$\varepsilon_j \sim N(0, \sigma^2)$. Let. $\theta \sim \varepsilon / \sigma$ Then $\theta_j \sim N(0,1)$ and

$$\Pr[\varepsilon_j < \alpha z_j - \beta t_j] = \Pr[\theta_j < \frac{\alpha z_j}{\sigma} - \frac{\beta}{\sigma} t_j] = \Phi\left(\frac{\alpha z_j}{\sigma} - \frac{\beta}{\sigma} t_j\right)$$

The log-likelihood is

$$\ln L = \sum_{j=1}^{T} I_J \ln\left[\Phi\left(\frac{\alpha z_j}{\sigma} - \frac{\beta}{\sigma} t_j\right)\right] + (1 - I_j)\ln\left[1 - \Phi\left(\frac{\alpha z_j}{\sigma} - \frac{\beta}{\sigma} t_j\right)\right]$$

II. Contingent Valuation: Basic Model

CV-RUM

Calculating WTP

$$\alpha_1 z_j + \beta(y_j - WTP_j) + \varepsilon_{1j} = \alpha_0 z_j + \beta y_j + \varepsilon_{0j}$$

Solving this equation for WTP yields

$$WTP_j = \frac{\alpha z_j}{\beta} + \frac{\varepsilon_j}{\beta}$$

Two popular measures:

1) Mean WTP:

$$E_\varepsilon(WTP_j) = \frac{\alpha z_j}{\beta}$$

2) Median WTP:

$$\Pr[\alpha_1 z_j + \beta(y_j - M_\varepsilon(WTP_j)) + \varepsilon_{j1} = \alpha_0 z_j + \beta y_j + \varepsilon_{j0}]$$

$$= \Pr[M_\varepsilon(WTP_j) > \frac{\alpha z_j}{\beta} + \frac{\varepsilon_j}{\beta}] = 0.5$$

Ⅱ. Contingent Valuation: Basic Model
CV-RUM

<u>With a Log-Linear in Income Model</u>

$$v_j(y_j, z_j) = \alpha_i z_j + \beta \ln(y_j - t_j), i = 0,1$$

$$v_{1j} - v_{0j} = (\alpha_1 - \alpha_0)z_j + \beta \ln(y_j - t_j) - \beta \ln y_j = \alpha z_j - \beta \ln\left(\frac{y_j - t_j}{y_j}\right), \alpha = \alpha_1 - \alpha_0$$

$$\Pr(yes_j) = \Pr[\varepsilon_j < \alpha z_j - \beta \ln\left(\frac{y_j - t_j}{y_j}\right)]$$

$$= \Phi\left(\frac{\alpha z_j + \beta \ln\left(\frac{y_j - t_j}{y_j}\right)}{\sigma}\right)(probit)$$

WTP can be defined as

$$\alpha_1 z_j + \beta \ln(y_j - WTP_j) + \varepsilon_{1j} = \alpha_0 z_j + \beta \ln(y_j) + \varepsilon_{0j}$$

Solving this equation for WTP yields

$$WTP_j = y_j - y_j \exp(-(\frac{\alpha z_j}{\beta} + \frac{\varepsilon_j}{\beta}))$$

$$E_\varepsilon(WTP_j) = y_j - y_j \exp\left(-(\frac{\alpha z_j}{\beta} + \frac{1}{2}\frac{\sigma^2}{\beta^2})\right) \qquad M_\varepsilon(WTP_j) = y_j - y_j \exp\left(-\frac{\alpha z_j}{\beta}\right)$$

Now, E_ε and M_ε can be very different from each other.

Ⅱ. Contingent Valuation: Basic Model

CV-Random WTP

Random Utility vs. Random WTP

Rather than modelling the indirect utility function and then deriving the appropriate WTP measure, many researchers have emphasized directly modelling the WTP function. The WTP function approach is equivalent to the utility function approach in a dichotomous CV study. However, those two approaches are not equivalent in either of the following cases:

1) Unlike the utility function approach, the WTP function approach allows multiple-bounded questions.

2) A multiple choice model (CRM or conjoint model) can be analyzed only with the utility function approach.

The WTP function: $WTP(y_j, z_j, \varepsilon_j)$

The probabilities of saying yes:

$$\Pr[WTP(y_j, z_j, \varepsilon_j) > t_j] = \Pr[v_1(y_j - t_j, z_j) + \varepsilon_{1j} > v_0(y_j, z_j) + \varepsilon_{0j}]$$

II. Contingent Valuation: Basic Model
CV-Random WTP

With a Linear WTP Function

$$WTP(z_j, \eta_j) = \gamma z_j + \eta_j$$

$$\Pr(yes_j) = \Pr(WTP > t_j) = \Pr(\gamma z_j + \eta_j > t_j) = \Pr(-(\gamma z_j - t_j) < \eta_j) = \Pr(\gamma z_j - t_j > \eta_j)$$

$$= \Pr(\frac{\gamma z_j - t_j}{\sigma} > \theta_j), \eta \sim N(0, \sigma^2), \theta \sim N(0,1)$$

The expected WTP:

$$E_\eta(WTP : z_j, \gamma) = \gamma z_j$$

Using the estimated coefficients $\widehat{\left(\frac{\gamma}{\sigma}\right)}$ and $-\widehat{\left(\frac{1}{\sigma}\right)}$, we derive a consistent estimates of the expected WTP,

$$E_\eta(WTP : z_j, \gamma) = \frac{\widehat{\left(\frac{\gamma}{\sigma}\right)}}{\widehat{\left(\frac{1}{\sigma}\right)}} z_j$$

II. Contingent Valuation: Basic Model
CV-Random WTP

<u>With an Exponential WTP Function</u>

$$WTP(z_j, \eta_j) = \exp(\gamma z_j + \eta_j)$$

$$\Pr(yes_j) = \Pr(WTP > t_j) = \Pr(\exp(\gamma z_j + \eta_j) > t_j) = \Pr(\gamma z_j + \eta_j > \ln(t_j)) = \Pr(\gamma z_j - \ln(t_j) > \eta_j)$$

$$= \Pr\left(\frac{\gamma z_j - \ln(t_j)}{\sigma} > \theta_j\right), \eta \sim N(0, \sigma^2), \theta \sim N(0,1)$$

Again, the mean and the median can be very different from each other.

$$E_\eta(WTP : z_j, \gamma) = \exp\left[\frac{\left(\widehat{\frac{\gamma}{\sigma}}\right)}{\left(\widehat{\frac{1}{\sigma}}\right)} z_j + \frac{1}{2\left(\widehat{\frac{1}{\sigma}}\right)^2}\right] \qquad M_\eta(WTP : z_j, \gamma) = \exp\left[\frac{\left(\widehat{\frac{\gamma}{\sigma}}\right)}{\left(\widehat{\frac{1}{\sigma}}\right)} z_j\right]$$

Ⅱ. Contingent Valuation: Basic Model

The Dispersion of WTP

$$E_\eta(WTP : z_j, \gamma) = \frac{\left(\frac{\widehat{\gamma}}{\sigma}\right)}{\left(\frac{\widehat{1}}{\sigma}\right)} z_j$$

is a random variable because both $\left(\frac{\widehat{\gamma}}{\sigma}\right)$ and $-\left(\frac{\widehat{1}}{\sigma}\right)$ are random.

Derive the intervals of E_η :

1) Delta method: linear approximation of E_η : $WTP(\beta) = f(\beta), V(WTP) = \left(\frac{\partial f}{\partial \beta}\right)' V(\beta) \left(\frac{\partial f}{\partial \beta}\right)$

2) Krinsky and Robb method: a Monte Carlo simulation method, draws N observations on the parameter vector from the estimated multivariate normal distribution of the parameters,

$$V(\widehat{\beta}) = \left[\frac{-E\partial^2 \ln L(\widehat{\beta})}{\partial\beta \cdot \partial\beta'}\right]^{-1}$$

At each draw, WTP is calculated .

III. Contingent Valuation: Extension

Double-bounded Models

Potential Efficiency Gains

In a double-bounded CV respondents are presented with initial bid prices. Following their initial responses, they are given new prices, lower if their initial responses were "no", higher if the responses were "yes" (Hanemann et al., 1991). Double-bounded models increase efficiency over single-bounded models but may increase the risk of strategic bias.

The bounds on WTP are

1) $t^1 < WTP \leq t^2$ For the "yes-no" responses;

2) $t^1 > WTP \geq t^2$ For the "no-yes" responses;

3) $WTP \geq t^2$ For the "yes-yes" responses;

4) $WTP \leq t^2$ For the "no-no" response.

III. Contingent Valuation: Extention

Double-bounded Models

Bivariate Model

WTP in each question is allowed to be different: $WTP_{ij} = \mu_i + \varepsilon_{ij},\ j = 1,2$

$$L_i(\mu|t) = \Pr(\mu_1 + \varepsilon_{1j} \ge t^1, \mu_2 + \varepsilon_{2j} < t^2)^{YN} \times \Pr(\mu_1 + \varepsilon_{1j} \ge t^1, \mu_2 + \varepsilon_{2j} \ge t^2)^{YY}$$

$$\times \Pr(\mu_1 + \varepsilon_{1j} < t^1, \mu_2 + \varepsilon_{2j} < t^2)^{NN} \times \Pr(\mu_1 + \varepsilon_{1j} < t^1, \mu_2 + \varepsilon_{2j} \ge t^2)^{NY}$$

$$\Pr(\mu_1 + \varepsilon_{1j} < t^1, \mu_2 + \varepsilon_{2j} < t^2) = \Phi_2\left(\frac{t^1 - \mu_1}{\sigma_1}, \frac{t^2 - \mu_2}{\sigma_2}, \rho\right) : \text{no} - \text{no}$$

$$\Pr(\mu_1 + \varepsilon_{1j} < t^1, \mu_2 + \varepsilon_{2j} \ge t^2) = \Phi_2\left(\frac{t^1 - \mu_1}{\sigma_1}, \frac{t^2 - \mu_2}{\sigma_2}, -\rho\right) : \text{no} - \text{yes}$$

$$\Pr(\mu_1 + \varepsilon_{1j} \ge t^1, \mu_2 + \varepsilon_{2j} < t^2) = \Phi_2\left(-\frac{t^1 - \mu_1}{\sigma_1}, \frac{t^2 - \mu_2}{\sigma_2}, -\rho\right) : \text{yes} - \text{no}$$

$$\Pr(\mu_1 + \varepsilon_{1j} \ge t^1, \mu_2 + \varepsilon_{2j} \ge t^2) = \Phi_2\left(-\frac{t^1 - \mu_1}{\sigma_1}, \frac{t^2 - \mu_2}{\sigma_2}, -\rho\right) : \text{yes} - \text{yes}$$

III. Contingent Valuation: Extension
Double-bounded Models

Interval Data Model

$$WTP_j = \mu_j + \varepsilon_j$$

$$Pr(yes, yes) = Pr(WTP_j > t^1, WTP_j \geq t^2) = Pr(\mu_j + \varepsilon_j \geq t^2)$$

$$Pr(no, no) = Pr(WTP_j < t^1, WTP_j \leq t^2) = Pr(\mu_j + \varepsilon_j < t^2)$$

$$L_i(\mu|t) = Pr(t^2 - \mu_j > \varepsilon_j \geq t^1 - \mu_j)^{YN} \times Pr(\mu_j + \varepsilon_j \geq t^2)^{YY}$$
$$\times Pr(\mu_j + \varepsilon_j < t^2)^{NN} \times Pr(t^1 - \mu_j > \varepsilon_j \geq t^2 - \mu_j)^{NY}$$

Where, $$Pr(t^2 - \mu_j > \varepsilon_j \geq t^1 - \mu_j) = \Phi\left(\frac{t^2 - \mu_j}{\sigma}\right) - \Phi\left(\frac{t^1 - \mu_j}{\sigma}\right)$$

III. Contingent Valuation: Extension

Double-bounded Models: Examples

1) Single-bounded Model

y1	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
lt1	-.4105172	.0442763	-9.27	0.000	-.4972972	-.3237372
_cons	2.645757	.3542875	7.47	0.000	1.951366	3.340147

1	431.9884242
2	624.7867091
3	836.0724255

2) Bivariate Double-bound

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eq1						
lt1	-.4063023	.0439579	-9.24	0.000	-.4924583	-.3201464
_cons	2.61519	.3528893	7.41	0.000	1.923539	3.30684
eq2						
lt2	-.4745032	.0358563	-13.23	0.000	-.5447802	-.4042261
_cons	2.963073	.2948598	10.05	0.000	2.385159	3.540988
sig12						
_cons	1.351017	.0405321	33.33	0.000	1.271576	1.430459

III. Contingent Valuation: Extension

Double-bounded Models: Examples

3) Bivariate Double-bound with Homogenous Coefficients

(1) [eq1]_cons - [eq2]_cons = 0
(2) [eq1]lt1 - [eq2]lt2 = 0

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
eq1						
lt1	-.4110048	.0402752	-10.20	0.000	-.4899428	-.3320668
_cons	2.521126	.3210393	7.85	0.000	1.891901	3.150352
eq2						
lt2	-.4110048	.0402752	-10.20	0.000	-.4899428	-.3320668
_cons	2.521126	.3210393	7.85	0.000	1.891901	3.150352
sig12						
_cons	1.282113	.0531317	24.13	0.000	1.177976	1.386249

4) Interval Data Model

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Beta						
_cons	6.38417	.1125676	56.71	0.000	6.163542	6.604799
Sigma						
_cons	2.113841	.1162686	18.18	0.000	1.885959	2.341723

III. Contingent Valuation: Extension
Spike Models

In any CV study, there is some likelihood that survey procedures will encounter respondents who do not care about the scenario being described (zero WTP):

Indifferent Respondents Can Be Identified

Define p as the probability of indifference

$$L_j(t) = p^Z((1-p)\cdot \Pr(N))^N \cdot ((1-p)\Pr(Y))^Y$$

where Z=1 if the respondent is indifferent and zero otherwise. N = 1 if a 'no' response is recorded by a non-indifferent respondent, Y=1 if a 'yes' responses is recorded by a non-indifferent respondent (N+Y+Z=1). Rearranging yields:

$$L_j(t) = p^Z(1-p)^{N+Y} \cdot \Pr(N)^N \cdot \Pr(Y)^Y$$

$$\ln L = \sum_{i=1}^{M} Z_i \ln p + \left(M - \sum_{i=1}^{M} Z_i \right) \ln(1-p) + \sum_{Z_i=0} \left[N_i \Pr(no|t_i) + Y_i \Pr(yes|t_i) \right]$$

Noting that N+Y is an indicator of positive WTP, we see that the model separates into two distinct discrete choice models.

III. Contingent Valuation: Extension

Spike Models

Indifferent Respondents Cannot Be Identified

$$L_j(t) = \left(p + (1-p)\Pr(N)\right)^{N_T} \cdot \left((1-p)\Pr(Y)\right)^{Y}$$

where N_T indicates a 'no' response for any reason (indifference or WTP < t). In this model the estimation of the yes/no response cannot be separated from the estimation of the model of indifference.

Kriström (1997)'s Spike Model

$$F_{WTP}(A) = 0 \quad \text{if } A<0 \qquad F_{WTP}(A) = 0$$

$$p \quad \text{if } A=0 \qquad F_{WTP}(A) = [1+\exp(\alpha)]^{-1}$$

$$G_{WTP}(A) \quad \text{if } A>0 \qquad F_{WTP}(A) = [1+\exp(\alpha - \beta A)]^{-1}$$

Identifying and dropping protest responses

The procedure is arbitrary.

There is an issue of sample selection bias.

III. Contingent Valuation: Extension

Ranking or Choice Models

The choice experiment asks individuals to provide more information about their preferences by giving them more alternatives than the discrete choice approach and by asking them either to select their most preferred option or to rank the alternatives in order of preferences (contingent ranking). Each alternative could have several different attributes one of which has a monetary dimension.

Estimation Methods

1) Conditional Logit

$$\Pr[u_i > u_j, \text{for } \forall j \neq i] = \frac{\exp(v_i)}{\sum_{j=1}^{N} \exp(v_j)}$$

2) Mixed Logit

$$P_{ni} = \int \left(\frac{\exp(\beta' x_{ni})}{\sum_{j=1}^{J} \exp(\beta' x_{nj})} \right) f(\beta) d\beta$$

3) Multinomial Probit, Latent Class Model, etc.

III. Contingent Valuation: Extension
Ranking or Choice Models: Examples

Example: Kwon (2006): Rafting in Hantan River

Attributes	Levels
1) Duration	45 min, 90 min, 150 min
2) Price	10,000, 20,000, 40,000
3) No. Torrents	4, 7, 10
4) Turbidity	Clean, Turbid
5) Weather	Clean, Rain, Cloudy
6) Waiting Time	10 min, 20 min, 30 min
7) No. Of Lifeguards on Board	1, 2, 3
8) Parking Space	Available, Not Available
9) Expert Explanation on the Scenery	Available, Not Available

III. Contingent Valuation: Extension

Ranking or Choice Models: Examples

<u>Example: Kwon (2006): Rafting in Hantan River</u>

☞ Suppose that you could choose only one of the following rafting courses today. Then what would be your choice?

	A	B	C
1) Duration	45 min	90 min	I will choose neither of them. I would do something else instead of going rafting.
2) Price	10,000	20,000	
3) No. Torrents	10	10	
4) Turbidity	Turbid	Turbid	
5) Weather	Clean	Rain	
6) Waiting Time	10 min	10 min	
7) No. Of Lifeguards on Board	1	1	
8) Parking Space	Available	Not Available	
9) Expert Explanation on the Scenery	Available	Not Available	
Choice(∨)	( )	( )	( )

Improvement in Turbidity	0.92 (10,000won per person)
Preventing Drought	2.48 (10,000won per person)
Preventing Flood	1.52 (10,000won per person)
Installing a Parking Lot	0.66 (10,000won per person)

III. Contingent Valuation: Extension
Nonparametric Method: Turnbull Estimation

The full sample T is divided into M subsamples T = {T_1, …, T_M}.
Y = {Y_1, …, Y_M}, and N = {N_1, …, N_M}, where Y_j (N_j) is the number of yes (no) response to bid price t_j.
The full likelihood function is

$$\Pr(F_1,\ldots,F_M,Y_M,N_1,\ldots,N_M) = \prod_{j=1}^{J} \binom{T_j}{Y_j} F_j^{N_j}(1-F_j)^{Y_j}$$

The MLE estimates, $F_j = \dfrac{N_j}{T_j}$

The density, $f_j = F_j - F_{j-1}$

The WTP estimates, $E_{LB}(WTP) \sim N\left(\sum_{j=0}^{M^*} t_j[F_{j+1}^* - F_j^*], \sum_{j=1}^{M^*} \dfrac{F_j^*(1-F_j^*)}{T_j^*}(t_j - t_{j-1})^2\right)$

If the response is not monotonic, then apply a Kuhn-Tucker condition to derive the MLE estimates.

III. Contingent Valuation: Extension

Additional Topics

Combining RP and SP

Incorporating Response Uncertainty

Turnbull with Covariates

Validity Tests (Exxon Valdez 1989: BP Deep Horizon 2010)

Criterion Validity
Convergent Validity
Construct Validity
Content Validity

Benefit Transfer

Unit Transfer
Function Transfer
Meta Analysis