Analysis of the relationship between risk perception and willingness to pay about nuclear power plant

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Abstract: As new technologies are invented, modern society is full of risk. Therefore, important decisions about new technologies tend to be made by specialists. These kinds of decision making process lead to mismatch of trust between citizens and specialists. It can be a reason of waste of social cost like the case of Gyeongju radioactive waste processing facility. In this paper, the relationship between willingness to pay (WTP) and risk perception which is deducted from image score, safety score and scientific background score about NPP was analyzed by contingent valuation method. Furthermore, quantitative relationship of them was drawn. Results indicated that scientific background level could make meaningful difference of image and safety score. Also, mean WTP was affected by scientific background level and image level. However, in image level case, it need to be consider not only image score but also zero bid people's percentage to analyze mean WTP. Therefore, when decision makers make policy, they need to consider the way to solve mismatch of trust between public and them.

Keyword: Nuclear energy; risk perception; willingness to pay; contingent valuation method

1 Introduction

As society becomes complex, new technologies are invented and interact each other [1]. Therefore, some interest groups come into conflict to achieve their goal. Especially, there is nuclear energy supporters and opponents' sharp conflict in Korea [2]. For example, to decide to build radioactive waste processing facility in Gyeongju, Korea government and nuclear operator, KHNP, spent almost 20 years. In this situation, it will bring about waste of huge money and time [3]. Thus, public consensus is important.

In nuclear energy field, the role of experts is essential to make social agreement because of its complexity and specialty [4]. However, risk perception between the experts and the public is different. The experts define risk according to its quality like its likelihood. On the other hand, the public define it according to its quantity like its hazard, genetic heritability [5]. This mismatch cause problem in risk communication between two groups.

According to Slovic et al. (1984; 1985), there are 7 kinds of risk characteristics and it is categorized as two groups, dread and unknown characteristics [6]. He suggested that when a risk is not fearful and well known, people will have low risk perception. Furthermore, previous research showed that risk perception affects people's willingness to pay (WTP) to reduce nuclear power plant (NPP)'s risk [7]. This paper explained that well defined risk communication is needed to reduce negative risk perception about nuclear energy which will be crucial factor to decide WTP.

However, it does not discussed that which factor of risk perception can affect WTP and their relationship. If decision makers know how people decide to pay, they can make strategy to raise WTP.

Therefore, in this study, relationship between image level which is a representative of the dread group from Solvic's study and WTP about NPP was verified. In addition, safety level was also included as comparative group. As a result, the factor which can affect to WTP was investigated either image level or safety level in this study.

Furthermore, there were three groups according to scientific background level. By analyzing each group's WTP, relationship of scientific information and WTP can be assessed.

2 Methods

2.1 Contingent valuation method

Contingent valuation method (CVM) is an analytical method for estimation subjects' value for non-market goods. In this method, estimation data in hypothetical market is used instead of that of real market. Therefore, researchers need to set hypothetical market and investigate respondent's answer under several condition by using specially designed questionnaire [8].

Table 1 Process of CVM

Steps	Descriptions
Research target selection	Select non-market resources
Scenario selection	Create a hypothetical market
Survey questionnaire design	Make scenario to describe valued goods and elicit the WTP
Survey	Do preliminary survey before main survey
Analysis about result	Process raw data by proper software Estimate the WTP

There are several kinds of method for CVM, but, it has two formula briefly [9]. One is open ended and the other is closed ended. If a researcher uses an open-ended method, a respondent can write down his willingness to pay. Whereas, if a researcher uses closed-ended method, a respondent needs to select one option for his willingness to pay among researcher's suggestion. Therefore, researchers can design their questionnaire what they want. They can ask one time, two times, or more. When the questionnaire ask just one time, this method is single-bounded dichotomous choice (SBDC). If they ask one more question, it can be categorized as double-bounded dichotomous choice (DBDC). Each cases has pros and cons which are described in Table 2 [9].

Table 2 Comparison between SBDC and DBDC

Type	Advantage	Disadvantage
SBDC	Similar to natural selection mechanism in real market	Less information Low statistical efficiency
DBDC	More information High statistical efficiency	Probability of occurrence of various response bias Inconsistency

Therefore, to select a proper way for a research goal will be a main concern. In this research, DBDC was used to get high efficiency of data. Furthermore, if questionnaire design process has some mistake, it can be modified in DBDC method. Also, in this process, there are two models, utility difference model and valuation function model, which can analyze mean WTP. Because these are duality relationship, there is no superiority [10]. Thus, utility difference model is applied in this study.

2.1.1 Utility difference model

In utility difference model, binary response about suggested bid is modeled. Then, related parameters are estimated by maximum likelihood estimation (MLE). Finally, mean WTP or median WTP can be assessed according to distribution's characteristic and definition [11].

Utility function is whether a respondent is willing to pay or not. It has three variables j, m and S. Each individual's utility function is expressed as following:

$$u = (j,\, m;\, S) \tag{1}$$

where, j is the state of non-market resource (j=0 : no access to the resource, j=1 : access to the resource), m is individuals' income, S is vector of other observable attributes of the individual which might affect respondent's utility function (e.g. sex, age, etc.).

However, a crucial assumption is that, although the individual knows his utility function, $v(j,m;S)$ with certainty, it contains some components that are unobservable to econometric investigator; thus, it is treated by the investigator as stochastic.

$$u(j,m;S) = v(j,m;S) + \varepsilon_j \tag{2}$$

where, ε_j is unobservable components represented as the random variables with zero means.

$u(j,m;S)$ is indirect utility function, which depends on the observable characteristics of the individual such as income (m) and the individual characteristics (S).

When offered an amount of money, A, the respondent will accept the offer if:

$$\Pr\{\text{"yes"}\} = v(1,m-A;S) + \varepsilon_1 \geq v(0,m;S) + \varepsilon_0 = \Pr[\Delta v \geq \eta] \quad (3)$$

$$\Delta(A) = v(1,m-A;S) - v(0,m;S) \quad (4)$$

$$\eta = \varepsilon_0 - \varepsilon_1 \quad (5)$$

Also, it can be converted by using cumulative density function of logistic distribution.

$$\Pr\{\text{"yes"}\} = \Pr(j=1) = \Pr[\Delta v \geq \eta] = F_\eta[\Delta v] \quad (6)$$

$$\Pr\{\text{"no"}\} = \Pr(j=0) = \Pr[\Delta v \leq \eta] = 1-F_\eta[\Delta v] \quad (7)$$

where, F_η $[\Delta v]$ is the cumulative distribution function(CDF) of η

Also, to convert this equation using WTP and requested amount, A :

$$\Pr\{\text{"yes"}\}=\Pr(j=1)=\Pr(WTP \geq A)=1-G_{WTP}(A) \quad (8)$$

$$\Pr\{\text{"no"}\}=\Pr(j=0)=\Pr(WTP<A)=G_{WTP}(A) \quad (9)$$

where, G_{WTP} (A) is the cumulative distribution function (CDF) of WTP.

$$G_{WTP}(A) = 1-F_\eta[\Delta v] = \frac{1}{1+e^{-\Delta v}} \quad (10)$$

For easy analysis, indirect utility function can be converted to an equation of the first using α and β.

$$(j,m;S) = a_j + \beta m \quad (11)$$

Also the difference between probability of yes and no.

$$\therefore \Delta v = v(1, m-A;S) - v(0,m;S) = [a_1+\beta(m-A)] - [a_0+\beta m] = \alpha - \beta \text{A} \quad (12)$$

$$G_{WTP}(A) = 1-F_\eta[\Delta v] = \frac{1}{1+e^{\alpha-\beta A}} \quad (13)$$

$$WTP_{mean} = \int_0^\infty [1 - G_{WTP}(A)]dA - \int_{-\infty}^0 G_{WTP}(A)dA = \frac{\alpha}{\beta} \quad (14)$$

2.1.2 Maximum likelihood estimation for SBDC

A purpose is to get the biggest WTP through finding α and β. In this process, a maximum likelihood estimation (MLE) will be used.

In MLE, unknown probability density function p(X; θ) and its joint density function is defined as following;

$$p(X;\theta) = p(x_1;\theta)p(x_2;\theta)\cdots p(x_N;\theta) = \prod_{i=1}^N p(x_i;\theta) \quad (15)$$

where, $\theta = [\theta_1, \theta_2, \cdots \theta_N]^T$ is vector of parameter for $p(X;\theta)$ and $X = \{x_1, x_2, \cdots x_N\}$ is 'n' samples of independent and identically distributed observations.

In the SBDC model, log likelihood function of WTP is derived as:

$$lnL = \sum_{i=1}^N (I_i^Y \ln[\Pr\{\text{"yes"}\}] + I_i^N \ln[\Pr\{\text{"no"}\}]) = \sum_{i=1}^N \{I_i^Y \ln[1 - G_{WTP}(A_i;\theta)] + I_i^Y \ln[G_{WTP}(A_i;\theta)]\} \quad (16)$$

$I_i^Y = 1$ (ith respondent's response is "yes")

$I_i^N = 1$ (ith respondent's response is "no")

$$\theta = (\alpha, \beta) \quad (17)$$

$$G_{WTP}(A_i;\theta) = \frac{1}{1+e^{\alpha-\beta A_i}} \quad (18)$$

Therefore, $\theta = (\alpha, \beta)$, which maximizes personal log likelihood function; $G_{WTP}(A;\theta)$, can be derived. Then, mean WTP also can be derived as following:

$$WTP_{mean} = \int_0^\infty [1 - G_{WTP}(A;\theta)]dA - \int_{-\infty}^0 G_{WTP}(A;\theta)dA = \frac{\alpha}{\beta} \quad (19)$$

2.1.3 Maximum likelihood estimation for DBDC

In DBDC model, researcher ask two questions. If respondent answer 'yes' when suggested bid is A_i, following question's bid will be A_i^u which is double amount of A_i. On the other hand, if respondent answer 'no' when suggested bid is A_i, following question's bid will be A_i^d which is half amount of A_i. Then, there are three kinds of bids; $A_i^u, A_i,$ and A_i^d.

Also, in this model, there are four kinds of answer type; Yes-Yes, Yes-No, No-Yes, No-No. Each case's probability is indicated as $\boldsymbol{\pi}$. For example, $\boldsymbol{\pi}^{YY}$ means that respondent's WTP is higher than A_i and lower than A_i^u . Then, it is derived as $\boldsymbol{\pi}^{YY}(A_i, A_i^u) = 1 - G(A_i^u)$.

By applying these probabilities to equation (16), the log likelihood function of DBDC is derived as following:

$$lnL = \sum_{i=1}^N \left(I_i^{YY} ln\, \boldsymbol{\pi}^{YY} + I_i^{YN} ln\, \boldsymbol{\pi}^{YN} + I_i^{NY} ln\, \boldsymbol{\pi}^{NY} + I_i^{NN} ln\, \boldsymbol{\pi}^{NN}\right) = \sum_{i=1}^N (I_i^{YY} ln\,[1 - G(A_i^u)] + I_i^{YN} ln\,[G(A_i^u) - G(A_i\ )] +$$

$$I_i^{NY} ln\,[G(A_i\ ) - G(A_i^d)] + I_i^{NN} ln\,[G(A_i^d)]) \quad (20)$$

As same as SBDC model,

$$WTP_{mean} = \frac{\alpha}{\beta} \quad (21)$$

2.1.4 Spike model

If there is high percentage of respondents' who have zero willingness to pay, spike model need to be applied. In spike model, there is one more question for No-No respondents. Researchers ask to them whether they really do not want to pay or not. When they really do not want to pay for resources, researchers need to modify their WTP equals to zero.

$$G_{WTP}(A;\theta) = \begin{cases} \frac{1}{1+\exp(\alpha-\beta A)} & if\ A > 0 \\ \frac{1}{1+\exp(\alpha)} & if\ A = 0 \\ 0 & if\ A < 0 \end{cases} \quad (22)$$

Then, spike that is the probability who do not want to pay is derived as:

$$\text{Spike} = \frac{1}{1+e^{\alpha}} \quad (23)$$

By applying spike model to DBDC log likelihood function, it is modified as following:

$$ln\,L = \sum_{i=1}^{N}(I_i^{YY} ln\,[1 - G(A_i^u)] + I_i^{YN} ln\,[G(A_i^u) - G(A_i\ )] + I_i^{NY} ln\,[G(A_i\ ) - G(A_i^d)] + I_i^{NNY} ln\,[G(A_i^d) - G(0)] + I_i^{NNN} lnG(0)]) \quad (24)$$

2.2 Design survey questionnaire for DBDC model

There were three questions in questionnaire, for applying DBDC model with spike. Researchers could suggest initial bid through first question. In this study, there were three questionnaire types with different bid. Then, according to respondent's answer, second question's bid was changed to double or half amount of initial bid. Third question was for No-No answer respondent to modify their CDF of WTP.

Furthermore, perception of image and safety about NPP was asked to verify relationship between them and WTP.

The method of survey is different according to group. For group 1 and 2, face to face investigation was selected. On the other hand, because of sample number and physical distance from researchers and respondents, internet survey was selected for group 3.

In survey, bid was suggested as a mean of payment of income tax for reducing hazard of NPP.

3 Results

3.1 General statistical data

There were 868 observations for survey. 868 observations can be categorized according to their basic statistical data like gender, age, etc. Those are expressed in Table 3.

Table 3 Basic statistical data

Characteristics		Observations [person]	Percentage [%]
Gender	Male	460	53.06
	Female	407	46.94
Age	10s	15	1.73
	20s	241	27.80
	30s	188	21.68
	40s	192	22.15
	50s	161	18.57
	60s	70	8.07
Education	High school	122	14.07
	College	635	73.24
	Graduate school	110	12.69
Income [$/month]	Below 500	206	23.76
	500-1000	48	5.54
	1000-1500	88	10.15
	1500-2000	96	11.07
	2000-2500	134	15.46
	2500-3000	55	6.34
	3000-3500	88	10.15
	3500-4000	18	2.08
	Above 4000	134	15.46

There were almost half male and female respondents. However, male percentage was slightly higher than female's. In age category, 20s was dominant, but the percentage gap with other age level was small. Over four fifth respondents are well educated. Furthermore, their income level was quite normally distributed except both ends.

Moreover, samples were divided into three groups according to scientific knowledge level about NPP. Group 1 was the people who are majoring in nuclear engineering. Group 2 was students in science or engineering department. Finally, group 3 was general people in Korea. They had variety of dwelling, income, age and education.

For each group, three types of questionnaire were randomly supplied and Table 4 is a summary of questionnaire distribution.

Table 4 Questionnaire design

Group	Questionnaire type	Bid [$]	Observations (Obs) [person]	Total obs
	A	5	9	
1	B	10	14	31
	C	20	8	
	A	5	11	
2	B	10	6	29
	C	20	12	
	A	5	264	
3	B	10	288	807
	C	20	255	

Fig.1 and Fig.2 are image and safety level of observations.

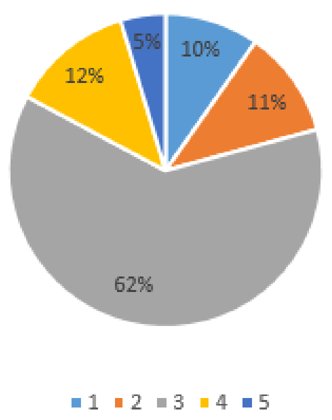

Fig.1 Image level

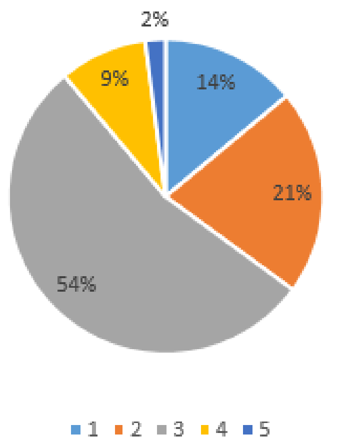

Fig.2 Safety level

While number 1 means bad image or unsafe, number 5 means good image or safe. More than half of respondents are in the middle of level in both cases. However, although almost 20 percent of people had positive image about NPP, only 10 percent of people thought that NPP is safe. Furthermore, 35 percent of people thought NPP is unsafe.

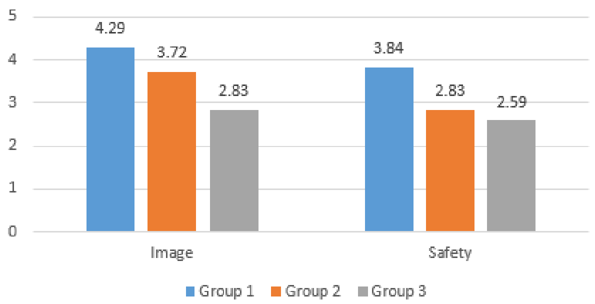

Fig.3 Perception about NPP’s property

According to group, perception of image and safety is different as shown in Fig.3. Understandably, the more scientific background they had, the better perception would be.

3.2 Mean willingness to pay

3.2.1 Mean WTP according to image level

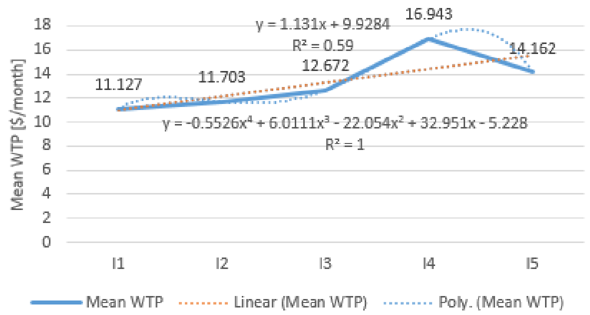

Fig.4 Image level

Mean WTP is assessed by using DBDC method with spike and without spike model. Mean WTP from each method was almost same. In order to avoid confusing, WTP from DBDC without spike model was omitted in Fig. 4.

In the case of image level, mean WTP increases corresponding to increasing of image level. Detailed number and trend is described in Fig.4. Therefore, it can be said that the people who have good image about NPP tend to have higher WTP than the people who have bad image.

However, there is an irregular peak in image level 4. The reason why it has peak is that low income people who are students or dependent on their parents were half of that level. Therefore, they assessed WTP without any concern. Then, their WTP has distance from reality.

To find best fit regression of the function between image level and mean WTP, various kinds of function regression was applied. There is Table 5 which describes regression result. Power function can describe trend quiet well. Also, polynomial functions can describe it.

From the point of view of image level, if people have good image, that is to say that they have low risk perception, their WTP will be high. It is contrary to previous study. The reason why this situation happened is can be found from the ratio of people who did not want to pay.

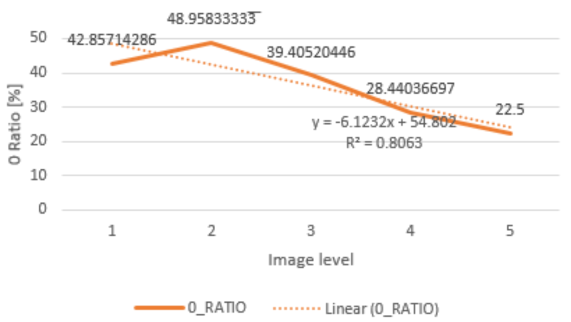

Fig.5 Zero bid ratio according to image level

As shown in Fig.5, at low image level, the ratio of people who did not want to pay for NPP hazard was much higher than the other cases. Therefore, their mean WTP could be much lower than other levels. Also, the most common reason why they did not want to pay was distrust about government and KHNP. Then, in the case of image level, analysis with risk perception and WTP was hard. There was correlation between image level and zero bid ratio.

3.2.2 Mean WTP according to safety level

Like image level case, mean WTP which is described in Fig.6 came from DBDC with spike model. However, there is no clear trend between safety level and mean WTP. Slope of linear regression was almost zero and R^2 value was also small.

As same as image level case, best fit regression function analysis was done in this case and its result is described in Table 6. Except polynomial function, linear function can give good description in safety level case.

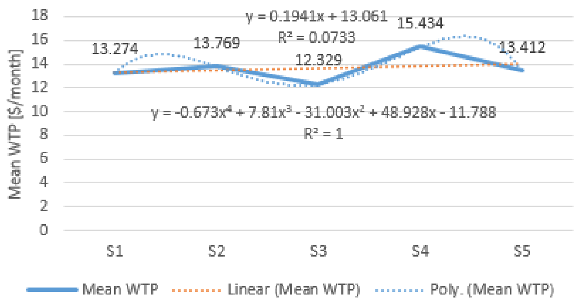

Fig.6 Safety level

Table 5 Various regression of WTP according to function type in the case of image level

Type		Function	R^2
Exponential		$y = 10.197e^{0.0852x}$	0.6454
Linear		$y = 1.131x + 9.9284$	0.5900
Logarithm		$y = 2.8092\ln(x) + 10.632$	0.5881
	Order: 2	$y = -0.2437x^2 + 2.5933x + 8.2224$	0.6284
Polynomial	Order: 3	$y = -0.6204x^3 + 5.34x^2 - 12.049x + 18.645$	0.8841
	Order: 4	$y = -0.5526x^4 + 6.0111x^3 - 22.054x^2 + 32.951x - 5.228$	1.0000
Power		$y = 10.749x^{0.212}$	0.6452

Table 6 Various regression of WTP according to function type in the case of safety level

Type		Function	R^2
Exponential		$y = 13.068e^{0.0135x}$	0.0684
Linear		$y = 0.1941x + 13.061$	0.0733
Logarithm		$y = 0.4655\ln(x) + 13.198$	0.0681
	Order: 2	$y = -0.0349x^2 + 0.4037x + 12.817$	0.0766
Polynomial	Order: 3	$y = -0.266x^3 + 2.3591x^2 - 5.8739x + 17.286$	0.2749
	Order: 4	$y = -0.673x^4 + 7.81x^3 - 31.003x^2 + 48.928x - 11.788$	1.0000
Power		$y = 13.2x^{0.0317}$	0.0613

3.2.3 Mean WTP according to scientific background level

As same as former analysis, DBDC with and without spike model were applied to assess mean WTP. The result of each method is almost same. DBDC with spike model's mean WTP is slightly lower than that of the other model. Respondents were divided to groups according to scientific background level. As expected, people who have higher background level had low mean WTP as we can verify in Table 7 and Fig.7.

Table 7 Mean WTP estimation

Category		DBDC without spike		DBDC with spike	
		α	β	α	β
Group 1	Coefficient	0.6508331	0.1496743	0.5495556	0.1460515
	z	1.51	3.88	1.59	4.73
	Mean WTP [$]	7.158		6.883	
	95% confidence interval [$]	3.987~10.328		3.712~10.053	
Group 2	Coefficient	1.1412831	0. 1489198	1.322493	0.1448168
	z	3.03	4.54	3.31	5.40
	Mean WTP [$]	10.950		10.763	
	95% confidence interval [$]	7.170~14.731		6.947~14.580	
Group 3	Coefficient	0.3980344	0.066729	0.3766498	0.0664314
	z	5.08	17.25	5.43	20.23
	Mean WTP [$]	13.665		13.534	
	95% confidence interval [$]	12.249~15.081		12.132~14.936	
Total	Coefficient	0.4351481	0.0710649	0.4095809	0.0706086
	z	5.74	18.32	6.11	21.02
	Mean WTP [$]	13.146		13.012	
	95% confidence interval [$]	11.866~14.426		11.731~14.293	

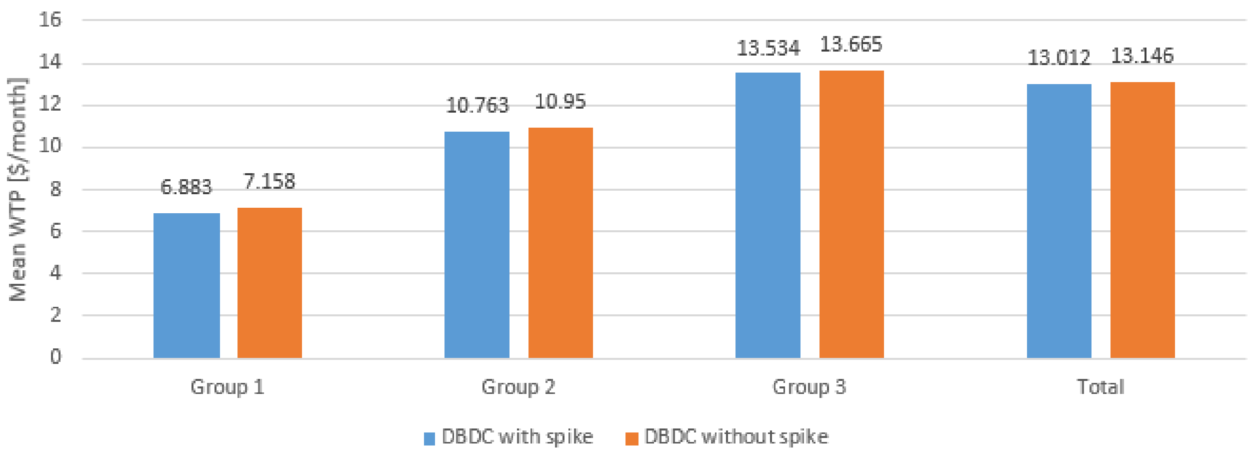

Fig.7 Mean WTP according to group

The most common reason why group 1 people did not want to pay was that there was no information to decide. On the other hands, the reason of group 2 was that payed tax need to be used to reduce hazard of NPP and that of group 3 was that government and KHNP make this problem on their own. Furthermore, the most interesting thing is minority opinions. At group 1, it was that NPP is fully safe. However, at group 2 and 3, the majority reason among minority opinions was distrust about government and KHNP. They believed that they will not use their tax for proper purpose.

Also, it is proved that the people who have enough scientific information, in other words, the people who have low risk perception, had lower WTP.

4 Conclusion

In this paper, specially designed questionnaire are used to find out the factor which can affect to WTP about NPP hazard reducing. As assumption, image level, safety level and scientific background level was selected as a factor. The result of survey was analyzed by CVM-DBDC method. There were two kinds of methods whether that DBDC method has spike or not. Two methods' mean WTP were almost same.

Naturally, the people who have more scientific background tended to good image about NPP and thought that NPP is safe. Coincidently, their WTP was lower than others. When mean WTP was analyzed according to image level, because of zero bid portion of low image level, its trend was inversely proportional to previous study's idea. Although the people who had low image level might feel that they are being threatened by NPP, because of disbelief about government and KHNP, their WTP to reduce risk was low. Therefore, to make policy for risk communication, decision makers need to think about obtaining people's belief.

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