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A Simple Way to Elicit Subjective Ambiguity:

Application to Low-dose Radiation Exposure in Fukushima

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Abstract: We develop a new and less burdensome methodology called the *high-and-low choice method* to elicit and analyse ambiguity in public risk perception. We apply this method to the cancer mortality risk due to low-dose radiation exposure around the Fukushima Daiichi nuclear power plant, a real uncertain problem caused by the accident that is the second severest one after the Chernobyl case. The empirical results shed new light on Slovic's (1987) seminal work; considering radiation as an *unknown* risk made public perceptions for the mortality rate more ambiguous, and the *dread* image led people to perceive larger and more ambiguous risks. In addition, those who accessed popular information media (television, newspaper, internet, social network services, and conversations with neighbours) tended to have more negative and ambiguous perceptions.

***Keywords*:** subjective ambiguity, belief elicitation, structural analysis, mortality rate, radiation exposure, Fukushima

1. INTRODUCTION

Revealing public risk perception as a cardinal measure poses an important challenge in order to analyse the huge discrepancy between the subjective and objective scientific assessments[1] or the causality from perception to preference in a meaningful way. The key issue is how to elicit true perception. However, this is not an easy task because, in many cases, people have never ponder about their own estimates of hazard occurrence probability, and stating such uncertain values precisely becomes burdensome. Excessive burden would make the measurement error extremely large, thus causing inefficiency and may lead to inconsistent parameter estimates of the structural model for risk perception. Therefore, researchers must always pay special attention to reduce this kind of burden.

Another challenge is to elicit subjective ambiguity. While the majority of risk perception studies implicitly assume that individuals can provide certain (or point) estimates, some studies have tried analysing individuals who are uncertain, but alternatively have second-order probability distributions, subjective likelihood distributions over the domain of hazard-occurring probability (referred to as *subjective distribution* in this paper). Those who are confronted with uncertainty conform to reality in many risk-related matters, and some approaches have been developed to elicit their ambiguities.

Our first contribution is to develop a less burdensome belief revealing method for the general public (hereafter *the high and low choice method*) and apply it to elicit Fukushima prefectural

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[1] See Sjöberg (1999) as an example of comparisons between public and experts' perceptions in qualitative measures such as a risk rating {0: none, 1: very small, …, 6: extremely large}. However, strict interpersonal comparisons are not possible since such measures have only ordinal meanings. See Viscusi and Hakes (2003) for more details about this problem.

residents' subjective ambiguities regarding mortality risk due to low-dose radiation exposure. As explained in subsection 3.1, reducing the burden is quite important in this case study.

Figure 1. Location of the Fukushima Daiichi Plant

The second contribution is to develop simple structural models of perceived uncertainty without any assumption on the shape of subjective distribution (even the uniform shape). In many uncertain cases, it is easy to imagine that each person has a different shape of his or her distribution: discrete or continuous, symmetric or asymmetric, unimodal, bimodal or trimodal, or some combination of them. The researchers cannot easily observe and distinguish this kind of cognitional diversity. To treat this problem, there would be at least two approaches. One is to adopt a more flexible shape assumption as the previous studies did – from the normal distribution (Cameron, 2005) to the beta distribution (Viscusi and Magat, 1992; Riddel and Shaw, 2006; Delavande, 2008) and the induced distribution (ID) (Hill *et al*., 2007; Riddel, 2009; Nguyen *et al*., 2010, Riddel, 2011). However, if adopting the beta distribution or the ID, we cannot consider possible persons who have discrete, trimodal, uniform or the other shapes. Therefore, even these flexible distributions are still restrictive to account completely for decision-making under uncertainty. Another approach, the distributional assumption-free model developed here, does not suffer from such a difficulty.

In addition, a more serious difficulty in applying the ID model lies in misreading the meaning of a parameter denoted as ω in Riddel (2009, 2011). The above studies using the ID model interpreted it as indicating *subjective ambiguity*, but in fact, it indicates interpersonal variation (*hetero-aspect*) in estimating the median of the subjective distribution. This detail is explained in subsection 3.2.

On the other hand, as mentioned in subsection 5.3, our approach gives us only limited information about subjective ambiguity – a tradeoff of avoiding any assumptions on distributional shape. In the same subsection, we discuss when and how we can use this limited information to analyse decision-making under uncertainty.

Despite of this limitation, our empirical results shed new light on the seminal work of Slovic (1987); considering radiation as an unknown risk made the respondents' risk perceptions more ambiguous, and the dread image led them to perceive larger and more ambiguous risks. In addition, those who accessed popular information media (television, newspaper, internet, social network services (SNS), and conversations with neighbours) in order to learn the health effects of radiation, tended to have more negative and ambiguous perceptions.

2. UNCERTAINTY FOR LOCAL RESIDENTS AFTER THE NUCLEAR POWER PLANT ACCIDENT

The Fukushima Daiichi nuclear power plant accident caused radioactive contamination over a wide area and cast dark shadows over the residents living there: evacuation, unemployment, reduced sales, property value losses, invidious discrimination, and so on. Among these, the health effects of radiation exposure continue to be the main common issue for most people. To reduce public exposure, citizens are prohibited to live in evacuation areas, where the annual dose is calculated to exceed 20 mSv. Based on the Act on Special Measures concerning the Handling of Radioactive Pollution (enacted August 2011), the national and local governments commenced full-scale decontamination projects January 2012 onwards (see Figures 3 and 6 for more details). Nevertheless, the residents' unease may continue unabated as they tend to have negative and ambiguous perceptions for this particular risk (described in section 4).

Such perceptive gaps could be caused by several reasons. First, most people are unfamiliar with radiation in spite of the fact that we are always exposed to background radiation; irrelevant to the accident, the national average exposure dose from the natural environment and in medical settings is 2.1 mSv/year and 3.9 mSv/year, respectively (Nuclear Safety Research Association, 2011). Most of the scientific knowledge about the health effects of radiation has not been shared with the public although Japan is the only nation to have suffered the aftermath of atomic bombings. Of course, this could be attributed to the highly technical nature of this knowledge.

Another reason making the problem complex is the fact that the health effects of low-dose exposure is not clear. Previous epidemiological surveys suggests that the carcinogenic rate significantly rises in proportion to exposure doses *exceeding 100 mSv*, but still have not proved *for less than 100 mSv* (e.g. Preston *et al*. (2003)). That is, we are actually facing the problem of uncertainty defined by Knight (1921). On the other hand, several theories have been proposed for low-dose radiation effects: the linear non-threshold model (Gofman, 1981), the bystander effect (Nagasawa and Little, 1999), the hormesis effect (Luckey, 1980), and so on. Different theories result in differing risk assessments, and this conflicting information might make public perception more ambiguous.[2]

The above situations are likely to impose additional welfare losses on the residents. As numerous experiments have detected, human beings tend to reveal some kind of preferences for risk and uncertainty, known as risk/ambiguity aversion or loving. Especially, we often observe ambiguity aversion in cases of low mean probability losses (see reviews by Camerer and Weber (1992) or Viscusi and Chesson (1999)) like the situation of our case study. Of course, it must be

[2] Unfortunately, some false rumours without scientific basis have also been spread through hearsay via the internet and SNS.

noted that the residents' welfare losses would strongly relate to their own risk perceptions, rather than to scientific assessments.

3. PREVIOUS METHODS

3.1. Belief Elicitation

So far, roughly two approaches have been proposed to elicit subjective ambiguity: direct and indirect approaches. An example of an indirect approach is the exchangeability method (Baillon, 2008; Abdellaoui *et al*., 2011). This method enables us to observe some points of each respondent's cumulative distribution function without imposing any assumption for the distributional shape. The drawback is that the iterative questions are sometimes quite burdensome for the respondents. Even if this is not so, these questions would become imprudent in cases of health- or mortality-related matters, since the questions treat such risks as targets of a gamble. For example, consider a case study where respondents are queried, 'which event do you want to bet 50 dollars on?: (i) less than 30% of people will catch a cold this winter or (ii) 30% or more will'.

In the direct approach, each respondent is simply asked to state his or her estimate. For instance, Riddel *et al*. (2003) asked respondents to state precise values of their point or their lowest and highest estimates of mortality rate caused by radioactive waste transportation (similar to the open-ended contingent valuation method (CVM)). In order to determine the probability for contracting nerve disease or lymphoma caused by environmental pollution, Viscusi and Magat (1992) asked a point estimate equivalent to ambiguous information of [x%, y%]. Delavande (2008) elicited some points of subjective cumulative function for the probability of getting pregnant. However, stating precise values of unknown matters would be difficult (like willingness-to-pay in the Exxon-Valdez case), which we believe must also be the case for this study for the reasons mentioned previously. On the other hand, concerning mortality rate due to arsenic contamination of tap water, Jakus *et al*. (2009) asked the respondents to choose values closest to their point or lowest and highest estimates from a list of probabilities (as with the payment card CVM). However, this method inevitably causes measurement errors. This could be why Nguyen *et al*. (2010), who used the same data as Jakus *et al*. (2009), could not obtain efficient and interpretable-signed estimates for some parameters in their structural analysis.

Alternatively, we could ask respondents to select an interval including their estimates of the rise in the cancer mortality rate due to additional radiation exposure, and thus, they would not need to state precise values. This interval-choice method stems from the double-bounded dichotomous choice CVM, but does not suffer from several problems specific to this type of CVM, such as yea-saying (Kanninen, 1995), nay-saying (Whitehead, 2002), and starting-point biases (Herriges and Shogren, 1996). Those problems are said to be caused by *sequential* questioning in order to observe one or two bounds of an interval including the true willingness-to-pay (i.e. exhibiting the starting bid and after that the follow-up bid). In contrast, our approach makes it possible to observe bounds of the interval *simultaneously*.

In addition, we presume that all respondents are fundamentally uncertain and therefore, have some kinds of subjective distribution (such people were called as *uncertain respondents* in Riddel *et al*. (2003)). Therefore, we asked each respondent to select two intervals: one including the lowest estimate, and the other, the highest. In contrast, Riddel *et al*. (2003) called those who could state their point estimates as *certain respondents* and assumed that some people could be classified as such in their case study. However, such people can be treated as specific cases in our presumption (i.e. their subjective distributions degenerate), and it would be preferable to think of them as rare cases in today’s Fukushima.

3.2. Structural Model

For empirical analyses on subjective ambiguity, in order to consider the possibility that the subjective distribution may have a skewed or bathtub shape, assuming the beta distribution is more appropriate than the normal distribution. However, according to Riddel (2009), there are two drawbacks: (i) the difficulty in identifying the global maxima of the likelihood function and even more seriously, (ii) the fixed relationship between the mean (central tendency of the distribution) and the variance (variability).

The ID model of Heckman and Willis (1977) is irrelevant to these problems. However, there is a technical issue. Here, we briefly review the Riddel's (2009) derivation to clarify matters.

The ID modeling starts by specifying the following latent variable model.

$$I = \mu + \omega - \varepsilon \text{ where } \varepsilon \sim N(0,1),\ \omega \sim N(0, \sigma_\omega^2), \text{ and } \varepsilon \perp \omega. \tag{1}$$

Hill *et al*. (2007) interpreted μ and ω as the median and ambiguity parameters respectively (Riddel (2009) and Nguyen *et al*. (2010) did the same). We will reconsider this point later. Based on equation (1), the respondent's estimate of hazard occurrence probability (π) and its cumulative function are derived as follows.

$$\pi = \Pr(I > 0) = \Phi(\mu + \omega). \tag{2}$$

$$H(\pi') = \Pr(\pi < \pi') = \Phi\left(\frac{\Phi^{-1}(\pi') - \mu}{\sigma_\omega}\right). \tag{3}$$

On the basis of the Heckman and Willis's labor force participation model (1977), which provided the foundation for the ID modeling, equation (2) is interpreted as an extended version of binary response models (logit and probit); in the ID model, the index function is replaced with a probability function. Parameterize μ and σ_ω as linear functions of observed factors (X and Z) respectively.

$$\mu = \beta' X + \nu_\mu. \tag{4}$$

$$\ln\sigma_\omega = \gamma' Z + \nu_\omega. \tag{5}$$

ν_μ and ν_ω are stochastic terms. Then, the conditional cumulative function is

$$H(\pi'|X, Z) = \Phi\left(\frac{\Phi^{-1}(\pi') - (\beta' X + \nu_\mu)}{\exp(\gamma' Z + \nu_\omega)}\right). \tag{6}$$

If we assume that the stochastic terms are bivariate normally distributed and put the restriction that $\ln\sigma_\omega \leq 0$ in order to exclude bimodal distributions, then the likelihood function for an uncertain respondent whose lowest and highest estimates are π^L and π^H respectively, is derived as follows.

$$L = \int_{-\infty}^{-\gamma' Z} \int_{R^H}^{R^L} \phi_2(\nu_\mu, \nu_\omega) d\nu_\mu d\nu_\omega, \tag{7}$$

where $R^L = \Phi^{-1}(\pi^L) - \beta' X$, $R^H = \Phi^{-1}(\pi^H) - \beta' X$, and $\phi_2(\cdot)$ is the bivariate normal density function.

This double integral form looking complex at a glance is caused by including the stochastic terms in equations (4) and (5), but excluding them makes another serious problem clear. Nguyen *et al*. (2010) did so and derived the following function.

$$H(\pi'|X, Z) = \Phi\left(\frac{\Phi^{-1}(\pi') - \beta' X}{\exp(\gamma' Z)}\right). \tag{8}$$

It must be noted that this cumulative function is also derived by considering *heteroskedasticity*. Now, reconsider the latent variable model of equation (1). $\omega - \varepsilon$ is the composite error term. As the variance of ε is common for all respondents, it is a homoskedastic error. On the other hand, this is not so for the variance of ω because of the specification in equation (5). In fact, if the heteroskedasticity is specified as $\omega|Z \sim N(0, \exp(2\gamma' Z))$, as with the heteroskedastic probit model in Wooldridge (2010, p. 601), then equation (8) is immediately derived. Therefore, in a natural interpretation, ω is only a heteroskedastic error, which does not represent the subjective ambiguity.[3] Our interpretations would also be supported form Heckman and Willis (1977) mentioned above, since they included these two errors to consider individual homogeneity and heterogeneity in estimating the sample mean functions for sequential labor force participation, respectively.

In summary, the previous studies using the ID approach estimated *hetero-aspect* (sample or interpersonal variability) in estimating $\mu = \beta' X$, instead of ambiguity (intrapersonal variability) – is it possible to interpret the interpersonal variability as ambiguity of the representative person in sample although such a person is not of our interest? Moreover, $\Phi(\mu)$ does not necessarily have a clear meaning as the median of subjective distribution, and it is interpreted just as something included in $[\pi^L, \pi^H]$.

In contrast, our modelling in section 5 has two advantages. First, it does not put any assumption on the shape of the subjective distribution. In other words, any shapes (even uniform, bimodal, trimodal or non-continuous) are allowed. Second, we constructed two models explicitly having the meanings of the median and range of the distribution respectively.

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[3] To understand the problem, consider the following two simple cases, where there are only two persons, and they are identical in X and Z. In the first case, they state the same $[\pi^L, \pi^H]$, and $\pi^H - \pi^L$ is large. Then, σ_ω is estimated to be *small* while their ambiguities are *large*. In the second case, the first person's range $(\pi_1^H - \pi_1^L)$ and the second person's $(\pi_2^H - \pi_2^L)$ were equally small, but $\pi_1^L - \pi_2^H > 0$ is large (the first person's estimate was even higher than the other's). Conversely, σ_ω is estimated to be *large* in contrast to their *small* ambiguities.

4. SURVEY DESIGN AND DATA

In order to observe the public risk perception for low-dose radiation exposure and its relevant factors, an internet questionnaire survey[4] was conducted from 17 to 21 January 2013. The researching subjects were residents over 15 years of age living in Fukushima Prefecture except the evacuation area (Figure 2), and 4,527 monitors were randomly selected. We began by explaining the purpose of the survey to them and described the content of the questions. In particular, they were informed that they would be asked to estimate the rise in cancer mortality rate due to additional exposure. Before answering, they were also requested to read an 8-page booklet explaining the meanings of fundamental terminologies (radiation, radioactivity, sievert, becquerel, etc.), half-lives of the main pollutants (iodine-131, cesium-134, and cesium-137), the kinds of the health effects (deterministic and stochastic effects), the scientific view that radiation exposure might cause cancers even for doses less than 100 mSv and that this possibility would be higher for young children, and the fact that the average Japanese citizen

[4] The internet has become the preferred medium for social surveys for several reasons: (i) the return rates are expected to be higher than mail surveys, because the subjects are sampled from a pool of people who contract with web research companies and embrace survey offers, (ii) in contrast to phone or interview surveys, the data quality does not depend on the interviewers' abilities, (iii) we can customize the questionnaire sheets to have the respondents answer all questions in correct manners (no one can omit answering any question, the lowest estimate of mortality rate cannot be higher than the highest, and so on), and (iv) we can measure the total time each respondent spent on answering the survey and then exclude those who spent extremely short times. Although the respondents were sampled from internet users only, this disadvantage has become less relevant over the years with the increasingly widespread use of the internet.

has been exposed to annual background exposure irrelevant to the accident (1.5 mSv/year from the natural environment and 2.3 mSv/year due to medical reasons[5]). The questionnaire consisted of twenty-seven questions regarding social, economic, and mental impacts of the accident, risk perception, needs for decontamination projects, and socioeconomic characteristics.

Figure 2. Objective Area and Radiation Dose Distribution (Air Dose Rate (μSv/hour))

In total, 1,973 (43.6%) subjects responded. However, we excluded 301 people who denied answering about their family income, and therefore, the final sample size was 1,672. This somewhat low return rate can be attributed to the fact that as our sample includes people who actually live in a contaminated environment, the questions regarding cancer mortality rate would have been stressful for them. Therefore, it is necessary to examine the representativeness of the sample. Table 1 shows a comparison with the official statistics for the socioeconomic characteristics of Fukushima residents. The high rate of male in our sample can be attributed to several reasons: more males might have answered as the representatives of their families because of the relic of patriarchal system, or females might have avoided answering because they are thought to be more risk-avoiding than males and, if so, they would have experienced higher stress levels for this survey. Many respondents were aged 30 to 50 years, which is a general tendency in internet surveys as these age groups use the internet more frequently for recreation and business. Our sample is also alike in terms of the low rate of single-person households, given that such households rarely participate in non-official surveys. The high rate

[5] These values differ from those in section 2, because we referred to an earlier report of the Nuclear Safety Research Association (2004) while preparing the booklet.

of respondents with family income less than 2 million yen could be attributed to the fact that the corresponding official statistical survey excluded single-person households from its research. It is important to interpret the analytical results while keeping these differences in mind.

Table I. Comparison with Official Statistics for the Socioeconomic Characteristics of Fukushima Residents

The procedure of risk perception elicitation was as follows. First, we presented two documents (Figure 3) in order to share common information concerning the changes in the national standards for the exposure dose for the general public and for the decontamination projects. Next, we emphasized concrete values, 1 and 20 mSv, which are the legal standards for radiation protection and also our target values for the elicitation.

Figure 3. Explanations before the Risk Perception Question

Then, almost half the respondents were asked to predict the rise in the cancer mortality rate due to an additional exposure of 1 mSv, and the other half were asked to predict the same for 20 mSv. Following Riddel *et al*. (2003) and Jakus *et al*. (2009), we provided a risk ladder (Figure 4) to assist their predictions.[6] Although these studies added scientific assessments for the target

[6] Risk ladders are popular graphical communication tools to help people understand the relative sizes of risks. However, they are known to influence their perceptions (see Nguyen *et al*. (2010) for more details). In addition, it must be noted that expressing probabilities as '*x* per million deaths' might be an inappropriate form of information provision or risk communication for the general public. Although we adopted such a frequency-based

risk on the ladder, we did not do so, because providing such a reference point would cause strong anchoring effects.

Figure 4. Risk Ladder

Figure 5 shows the actual format of the elicitation question. The interval alternatives were set to be mutually exclusive and exhaustive. Notably, the bounds of each interval were set on the basis of the risk ladder, so that respondents could directly refer to the ladder information. In addition, we customized the response format, whereby when predicting the highest rate, each respondent could not choose intervals lower than the lowest interval and vice versa (it was possible to choose the same interval for both bounds). The responses are summarized in Table 2.

Figure 5. Risk Perception Question (for an additional dose of 1 mSv)

Table II. Frequency Distribution of Risk Perceptions

For simple comparisons with scientific assessments, the median and range of each respondent were roughly calculated as follows. We denote respondent *i*'s lowest and highest estimates as π_i^{L*} and π_i^{H*} respectively, and these are latent variables. If he (or she) chose the *l*th interval as including π_i^{L*}, then the following relationship is satisfied.

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expression in this study because it is easy to understand, we accept that it might cause cognitive biases (known as *neglecting the denominator*) and make people overestimate small probabilities (see Slovic *et al*. (2000)).

$$\underline{\pi}_l \leq \pi_i^{L*} \leq \overline{\pi}_l \text{ if } i \text{ chose } l \; (l = 1, 2, \ldots, 16), \tag{9}$$

where $\underline{\pi}_l$ and $\overline{\pi}_l$ are the lower and upper bounds of the interval (note that $\underline{\pi}_1 = \overline{\pi}_1 = 0$). Likewise, a similar relationship is established for π_i^{H*}, if he chose the *h*th interval.

$$\underline{\pi}_h \leq \pi_i^{H*} \leq \overline{\pi}_h \text{ if } i \text{ chose } h \; (h \geq l), \tag{10}$$

where $\underline{\pi}_h$ and $\overline{\pi}_h$ are the bounds of the interval. Because the median of his subjective distribution is defined as $m_i^* \equiv (\pi_i^{L*} + \pi_i^{H*})/2$, averaging equations (9) and (10) derives

$$\frac{\underline{\pi}_l + \underline{\pi}_h}{2} \leq m_i^* \leq \frac{\overline{\pi}_l + \overline{\pi}_h}{2}. \tag{11}$$

The left- and right-hand sides can be interpreted as the minimum and maximum of his possible medians, and we call them *the least median* (LM) and *the greatest median* (GM) respectively. On the other hand, the respondent's range is defined as $r_i^* \equiv \pi_i^{H*} - \pi_i^{L*}$. Therefore, if $h > l$, substituting (9) from (10) derives the condition for r_i^*. If $h = l$, another condition is derived. That is,

$$\begin{gathered} \underline{\pi}_h - \overline{\pi}_l \leq r_i^* \leq \overline{\pi}_h - \underline{\pi}_l \text{ if } h > l, \\ \text{or } 0 \leq r_i^* \leq \overline{\pi}_h - \underline{\pi}_h \text{ if } h = l. \end{gathered} \tag{12}$$

Both sides in each condition can be interpreted as the minimum and maximum of possible ranges, and we call them *the least range* (LR) and *the greatest range* (GR) respectively.

In Table 2, we calculated the individual approximate median as (LM + GM)/2 and the range as (LR + GR)/2 (we assumed that $\overline{\pi}_{16} = 0.698793$, because the Japanese cancer mortality rate was already 0.301207 without additional exposure). Compared with the estimated rate based on the linear no-threshold model, respondents tended to extremely overestimate for both 1 and 20 mSv. However, there seemed to be no proportional relationship between the exposure dose and risk perception – the increase in the median or range of mortality rate due to an additional exposure of 1 mSv is not one-twentieth of that by 20 mSv. Rather, the perceived effect of 1 mSv was estimated to be much greater and more ambiguous.

Several factors could determine subjective distribution. In order to investigate the relationship, we asked about the variables shown in Table 3. In the structural analyses, we assumed that all these can affect both the median and the range. In contrast, Riddel (2009) and Nguyen *et al*. (2010) classified their independent variables into those that would relate only to perceived risk (median) and those only to ambiguity (which is, in fact, heteroskedasticity). For example, gender was assumed to influence only the median, and risk information, only ambiguity. However, such classification does not have much rationale and conviction. Why can we exclude beforehand the possibilities that gender may also influence ambiguity and so on?

Table III. Independent Variables

The variable selection was based on Sjöberg (2000) and Dosman *et al*. (2001), who widely reviewed the deterministic factors of public risk perception.

Slovic's (1987) cognitive map showed that public perception was determined by two dimensions of risks: *unknown* and *dread*. However, according to Sjöberg (2000), these factors do not always determine the perception or sometimes affect it negatively. In addition, past studies did not focus on the effects on ambiguity. To investigate these issues, we attempted to quantify *unknown* and *dread* by simply asking respondents whether the following sentences corresponded to their images – 'radioactivity was an unfamiliar and mysterious thing' and 'it was somehow a terrible thing'.[7] Only a few respondents stated *unknown* or *dread* contrary to

[7] Although *unknown* and *dread* are usually quantified by factor analysis, we avoided this traditional way, because it would have become burdensome for our respondents, and this kind

our expectation (21.9% or 16.6% respectively), although it might be because almost twenty months had passed after the accident.

Dosman *et al*. (2001) reviewed the empirical results for the following socioeconomic factors: gender, age, income, number of children, years of education, primary source of risk information, and political ideology (we excluded years of education and political ideology from among these factors, because we believed that it was a too delicate matter to ask these factors in this case). Dosman *et al*. (2001) found that females, older people, people with lower income, parents of younger children, and less educated people tended to perceive larger risks. However, the results pertaining to age and education level were not general. For example, while younger people may be more familiar with new risks, on the other hand, they may be more impressionable to warnings from others who perceive risks negatively. Less educated people may not be too conscious of several risks, but may feel more fear, because they do not know how to avoid or mediate the risks.

Unfortunately, the results for the socioeconomic factors have sometimes (or often) been interpreted in confounding ways. For example, Dosman *et al*. (2001) mentioned that 'as individuals' income levels increase, their overall perceptions of the world as a risky place decrease. This may be because they are able to purchase products to minimize their exposure to or mediate the level of risk'. We must note that they discussed the effect of income on risk preference (willingness-to-pay for risk avoidance) and not on perception.

In addition, there is scant evidence for the relationship between socioeconomic factors and ambiguity. Cameron (2005) suggested that females and younger people have a larger variance in each subjective distribution. Although Delavande (2008) investigated the influence of age,

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of quantification was not of our interest.

the results for the influence on variance were not clear because of the beta distribution assumption.

Risk information sources are also important factors influencing public perception. However, its effects are not clear and would vary accordingly to the time, place, and circumstance. For instance, the primary role of mass media (TV, newspapers, and so on) is to inform the public of risks and help their correct understandings, which is important to avoid their dangerous unconsciousness or extreme panic. Nevertheless, the media often cannot avoid providing incorrect information. On the other hand, many people seem to believe that governments and the a part of scientists often intentionally suppress negative information or have little concern for public health, and do not rely on these avenues of information (Jenkins-Smith and Silva, 1998).

To understand how our respondents gather information, we asked them ‘how do you and your family gather information regarding the health effects of radiation exposure’ and allowed them to choose multiple alternatives. In addition to the six alternatives described in Table 3, we also provided the following choices: ‘questioning your regular medical doctor’ and ‘questioning the relevant department of the national, prefectural, or municipal government’. However, a mere 4.7% and 3.7% respectively, chose these alternatives, and therefore, we excluded them from our analyses. The primary source of information was the TV and newspapers (55.0%), followed by the internet and SNS (29.2%), and conversation with neighbours (15.1%).

Moreover, we considered two other factors. The first was whether the respondents thought that there might be other health effects besides the carcinogenesis. The other factor was whether they lived in zones planned for decontamination. Municipalities in the intensive contamination survey areas described in Figure 6 researched where additional exposure dose was expected to exceed 1 mSv/year, specified the zones where decontamination was needed, and planned its implementation. However, we asked the question without presenting any relevant information such as Figures 2 and 6, since individual perceptions could have changed otherwise. About 52.3% of respondents were aware that they lived in the decontamination-planned zones, 26.1% were aware that they did not reside in such zones, and the rest were unaware.

Figure 6. Target Municipalities for Decontamination

The rates of having *unknown* and *dread* images, thinking possibilities of the other health effects, and gathering information are higher for those who knew that they lived in decontamination-planned zones (*decon zone* = 1). The higher rate of high family income for such respondents may have perhaps resulted from the fact that the distribution of relatively high-level contamination (green-coloured area in Figure 2) nearly coincided with a series of basins stretching along the Abukuma River, which were highly urbanized (e.g. the Fukushima and Kohriyama Cities, the largest cities in the prefecture) and the relatively high wage level.

5. MODEL SPECIFICATION

The median and range models were specified by expanding the interval data choice model of Hanemann *et al*. (1991).

5.1. Median Model

We assumed $m_i^* = \Phi(\mu_i)$ for each respondent i in order to assure $m_i^* \in [0,1]$ and specified the structure of μ_i as follows.

$$\mu_i = \beta' X_i + \nu_\mu, \ \nu_\mu \sim N(0,1) \tag{13}$$

where X_i is a vector of independent variables, β is a parameter vector, and ν_μ is the stochastic term. Then, based on equation (11), the contribution to the likelihood for respondent i was derived as

$$\begin{aligned} L_i^M &= \Pr(\mathrm{LM} \le m_i^* \le \mathrm{GM}) \\ &= \Phi(\Phi^{-1}(\mathrm{GM}) - \beta' X_i) - \Phi(\Phi^{-1}(\mathrm{LM}) - \beta' X_i). \end{aligned} \tag{14}$$

However, in order to compute the log-likelihood, two conditions must be satisfied: (i) $\mathrm{LM} > 0$ and $\mathrm{GM} > 0$, because the domain of $\Phi^{-1}(\cdot)$ is (0,1), and (ii) $\mathrm{GM} > LM$, because L_i^M must be larger than zero. The only case contrary to these conditions is the respondent choosing the first interval for both the lowest and the highest estimates ($\pi_i^{L*} = \pi_i^{H*} = 0$), in which case $\mathrm{LM} = \mathrm{GM} = 0$. Therefore, we replaced the likelihood for this case as follows. Among the other cases, LM is minimized when $l = 1$ and $h = 2$ (if $\pi_i^{L*} = 0$ and $0.000001 \le \pi_i^{H*} \le 0.000056$, then $\mathrm{LM} = 0.0000005$). Then, we assumed that the respondent's choice of $l = h = 1$ means that his or her median was lower than the minimum ($m_i^* < 0.0000005$)[8]. Finally, the likelihood was summarized as

$$L_i^M = \begin{cases} \Pr(m_i^* < 0.0000005) = \Phi(\Phi^{-1}(0.0000005) - \beta' X_i) & \text{if } l = h = 1, \\ \Pr(\mathrm{LM} \le m_i^* \le \mathrm{GM}) & \\ \quad = \Phi\left(\Phi^{-1}\left(\dfrac{\overline{\pi}_l + \overline{\pi}_h}{2}\right) - \beta' X_i\right) - \Phi\left(\Phi^{-1}\left(\dfrac{\underline{\pi}_l + \underline{\pi}_h}{2}\right) - \beta' X_i\right) & \text{otherwise.} \end{cases} \tag{15}$$

---

[8] Another approach is to combine the first and second intervals into a new interval [0, 0.000056]. In this case, if the subject's choice was $l = 1$ or 2 and $h = 1$ or 2, then $\mathrm{LM} = 0$, and condition (i) is violated. Therefore, we neglected LM and just considered $m_i^* \le \mathrm{GM}$ when computing the likelihood. However, the estimation results were not much different from the approach in the main text.

5.2. Range Model

Likewise, we assumed $r_i^* = \Phi(\omega_i)$ in order to assure $r_i^* \in [0,1]$ and specified the structure of ω_i as follows.

$$\omega_i = \gamma' X_i + \nu_\omega, \nu_\omega \sim N(0,1) \tag{16}$$

where γ is a parameter vector and ν_ω is the stochastic term. Then, equation (12) establishes the contribution of respondent *i* to the likelihood.

$$L_i^R = \Pr(\mathrm{LR} \leq r_i^* \leq \mathrm{GR}) = \Phi(\Phi^{-1}(\mathrm{GR}) - \gamma' X_i) - \Phi(\Phi^{-1}(\mathrm{LR}) - \gamma' X_i). \tag{17}$$

The similar conditions must also be satisfied: (iii) $\mathrm{LR} > 0$ and $\mathrm{GR} > 0$, and (iv) $\mathrm{GR} > LR$. These conditions are violated only when $l = h$. If $l = h$, then LR must be zero, and condition (iii) is violated. In particular, if $l = h = 1$, then GR is also equal to zero, and condition (iv) is violated. Therefore, we replaced the likelihood for these cases as follows. First, for $l = h \neq 1$, we neglected LR and just consider $r_i^* \leq \mathrm{GR}$ (note that $\mathrm{GR} = \overline{\pi}_h - \underline{\pi}_h$ in these cases). Second, for another case of $l = h = 1$, the same approach with the median model was applied. Among cases satisfying conditions (iii) and (iv), the LR is minimized when $l = 1$ and $h = 2$ (then, $\mathrm{LR} = 0.0000005$). Thus, we assumed that his or her choice of $l = h = 1$ meant that his or her range was lower than the minimum ($r_i^* < 0.0000005$). Finally, the likelihood was summarized as

$$L_i^R = \begin{cases} \Pr(r_i^* < 0.0000005) = \Phi(\Phi^{-1}(0.0000005) - \gamma' X_i) & \text{if } l = h = 1, \\ \Pr(r_i^* \leq \mathrm{GR}) = \Phi\left(\Phi^{-1}\left(\overline{\pi}_h - \underline{\pi}_h\right) - \gamma' X_i\right) & \text{if } l = h \neq 1, \\ \Pr(\mathrm{LR} \leq r_i^* \leq \mathrm{GR}) = \Phi\left(\Phi^{-1}\left(\overline{\pi}_h - \underline{}_l\right) - \gamma' X_i\right) - \Phi\left(\Phi^{-1}\left(\underline{\pi}_h - \overline{\pi}_l\right) - \gamma' X_i\right) & \text{otherwise.} \end{cases} \tag{18}$$

5.3. When or How Can We Use Range to Analyse Decision-Making under Uncertainty?

Range is a simple measure of perceived ambiguity, but as Larson (1980) pointed out, it is not a sufficient measure in many cases. Suppose that there are two persons having the same range $[\pi^L, \pi^H]$ but with different distributional shapes. For example, the first person has a unimodal shape while the second person has a uniform one. In this case, the first person puts some degree of confidence on a particular probability and is less ambiguous than the second person. Thus, only with the information of range, we cannot distinguish the difference between them.

This is the tradeoff of the assumption-free approach; we can obtain only limited information about subjective ambiguity while being able to avoid the constraints of distributional shape assumptions. Therefore, considering this tradeoff, characteristics of the uncertain situation and purpose of the study, researchers have to determine which approach is applied: the approach developed here or the traditional one assuming some distributional shape.

For example, recall the situation of Ellsberg's experiment (1961). The respondents did not have any information about a proportion of red (or black) balls in the uncertain urn. In other words, they were completely uncertain, and thus, many of them might imagined only a uniform likelihood distribution over [0, 1] about the probability of red ball. In this situation, range becomes an appropriate measure of subjective ambiguity (Becker and Brownson, 1964). We can easily create similar situations on a laboratory basis – especially gambles for which the respondents are informed only intervals of the winning probabilities (e.g., Becker and Brownson (1964), Yates and Zukowski (1976), Larson (1980), Curley and Yates (1985) and Kahn and Sarin (1988)). However, such a situation would be rare in the real world. We recognize that today's Fukushima would also be far from it but practiced the distributional-free approach in the next section as the first attempt.

Even when range is not a sufficient measure of subjective ambiguity, we can use it to analyse human preference if accepting the α-maxmin rule (Jaffray, 1989; Marinacci, 2002; Ghirardato *et al*. 2004) instead of accepting any distributional shape assumptions. For example, consider an α-maxmin person who is uncertain about whether a bad event will occur or not. That is, whatever the shape of his (or her) subjective distribution is, he considers only the worst and best cases in decision-making. Denote his status dependent indirect utility as V_1 if the hazard occurs and as V_0 if it does not. If his perception for the hazard-occurring probability ranges from π_i^{L*} to π_i^{H*}, the willingness-to-pay (WTP) for him to exclude the uncertainty is defined as

$$
\begin{aligned}
V_0(y-\mathrm{WTP}) &\equiv \alpha\cdot EV(y)|_{\pi=\pi_i^{H*}} + (1-\alpha)\cdot EV(y)|_{\pi=\pi_i^{L*}} \\
&= EV(y)|_{\pi=\pi_i^{L*}} - \alpha[EV(y)|_{\pi=\pi_i^{L*}} - EV(y)|_{\pi=\pi_i^{H*}}] \\
&= EV(y)|_{\pi=\pi_i^{L*}} - \alpha r^*[V_0(y) - V_1(y)]
\end{aligned} \tag{19}
$$

where $EV|_\pi \equiv \pi V_1 + (1-\pi)V_0$ is expected indirect utility, y is status quo income, and $\alpha \in [0,1]$ is a weight put on the worst case of $\pi = \pi_i^{H*}$. Since $V_0(y) - V_1(y) > 0$, his WTP increases with r^* if V_0 is an increasing function of y and $\alpha > 0$.

Especially, if WTP is included in the indirect utility in an additive way (for instance, $V_0(y-\mathrm{WTP}) = V_0(y) - \beta\ln\mathrm{WTP}$ where $\beta > 0$ is marginal utility of income), its function is derived as a somewhat simple from.

$$
\ln\mathrm{WTP} = \beta^{-1}(\pi_i^{L*} + \alpha r^*)[V_0(y) - V_1(y)] \tag{20}
$$

Despite of the above usage, we could not conduct CVM questions in the survey to ask WTP for excluding the radioactive contamination or willingness-to-accept for bearing the contamination because (i) it was quite difficult to find out ethical or moral validities for a hypothetical scenario that Fukushima residents were to pay the decontamination cost and (ii) their unease was thought to be too serious to accept in exchange for monetary compensations. Trials of welfare analyses using the range information are remained in the other case studies.

6. EMPIRICAL RESULTS

The estimation results are summarized in Table 4. First, we discuss column (1), in which all variables are considered.

Table IV. Estimation Results of the Median and Range Models

Significantly positive parameters on *d20mSv* in both models indicate that those who predicted a rise in the cancer mortality rate due to additional exposure of 20 mSv tended to perceive larger and more ambiguous risks than those predicting the same for 1 mSv. These are quite interpretable results.

Unknown and *dread* images for radioactivity positively relate to both perceived risk and ambiguity, although the parameter on *unknown* is not significant in the median model and is less significant in the range model. Notably, the results suggest that both images determined subjective ambiguity and add fresh evidence to a series of works pioneered by Slovic (1987).

The parameter on *other effects* is significantly positive in both models and indicates that those who thought of the possibilities of other health effects tended to perceive the cancer mortality rate as larger and more ambiguous.

The respondents who knew that they lived in zones planned for decontamination, that is, those who recognized that their living environment was contaminated to some degree, perceived larger and more ambiguous risk. The result in the median model is consistent with those of Riddel and Shaw (2006) and Riddel (2009), who showed that respondents living near the route of nuclear waste transportation perceived a larger mortality rate. It also agrees with Nguyen *et al*.'s (2010) findings for increased perceived risk on account of arsenic concentration in tap water.

Regarding the other socioeconomic factors, the risk perceptions of females and respondents with low income also tended to be more negative and ambiguous. Gender effect on ambiguity is consistent with Cameron (2005), who showed that females had larger variances under the normal distribution assumption. In addition, older respondents perceived larger risks.

Regarding risk information, the most popular media (*TV/newspaper*, *internet/SNS*, and conversations with *neighbours*) positively relate to both perceived risk and ambiguity, although we could not identify the kind of information gathered, particular programs watched, the extent to which these pieces of information conflicted with each other, and so on. In contrast, respondents who gathered information from relevant books had less ambiguous perceptions.

Importantly, it must be noted that we should interpret the results on information just as correlations with perceptions, and not as causalities, because the parameters might suffer from self-selection biases – those who perceived larger or more ambiguous risks might want to gather information more actively. On the other hand, we should also note that excluding information variables causes omitted variable biases. Compare columns (1) and (2); the parameter on *unknown* increases in both models when information variables are excluded. Taking the positive parameters on the popular media in column (1) into account, this upward bias is caused by positive correlations between *unknown* and information gathering (see Table 5). While these correlations seem to be counterintuitive as people should have gathered information to make up for their lack of knowledge, the result is not surprising because their unfamiliarity to radioactivity might have been amplified through information gathering in the situation mentioned in section 2. The increase of the parameter on *other effects* would suggest that gathered information makes people more conscious of the other health effects. Also, *decon area* is positively correlated with information variables, and its parameter increases in column (2).

Table V. Correlations between Information and Other Variables

7. CONCLUSION

This study developed new simple methods to elicit and analyse ambiguity in public risk perception and applied them to the problem of radiation exposure in Fukushima, which is a real uncertain problem. The empirical analyses suggested a potential for the expansion of the work by Slovic (1987) and of other works investigating the influences of socioeconomic factors on risk perception. The results suggesting that usage of popular risk information media relates to more negative and ambiguous perception seem to reflect reality in the given case, namely, the delay in sharing scientific knowledge pertaining to the health effects of radiation exposure, conflicting scientific beliefs regarding the effects of low-dose exposure, the shortage of epidemiological evidence, conflicting public information, false rumours, and so on. Because of these factors, the popular media could not exclude imprecise or conflicting information.

Our methodology is applicable for any unknown matters for which people cannot easily estimate precise values, such as probabilities for outcomes that rarely happen or have never occurred, willingness-to-pay for non-market goods, and so on.

We hope that this method will be applied in the future studies and that its potential drawbacks will be clarified and improved. For example, a clear drawback in our survey is that the median and range might systematically correlate to each other, because the ranges of the alternatives in Figure 5 were designed to become gradually larger on the basis of the risk ladder (nevertheless, the ladder itself would provide appropriate information in predicting the rate of new mortality risk, as it was constructed from real mortality data). Was the similarity between estimation results of the median and range models caused by this systematic correlation? Prior to that point, does the range or something else indicating ambiguity generally have a positive relation with the central tendency (median or mean)? To examine these questions, we propose to attempt to elicit risk perceptions in a gradually wider form like figure 5 for a part of sample and in an equal interval form for another part in order to compare the estimation results between them for future applications.

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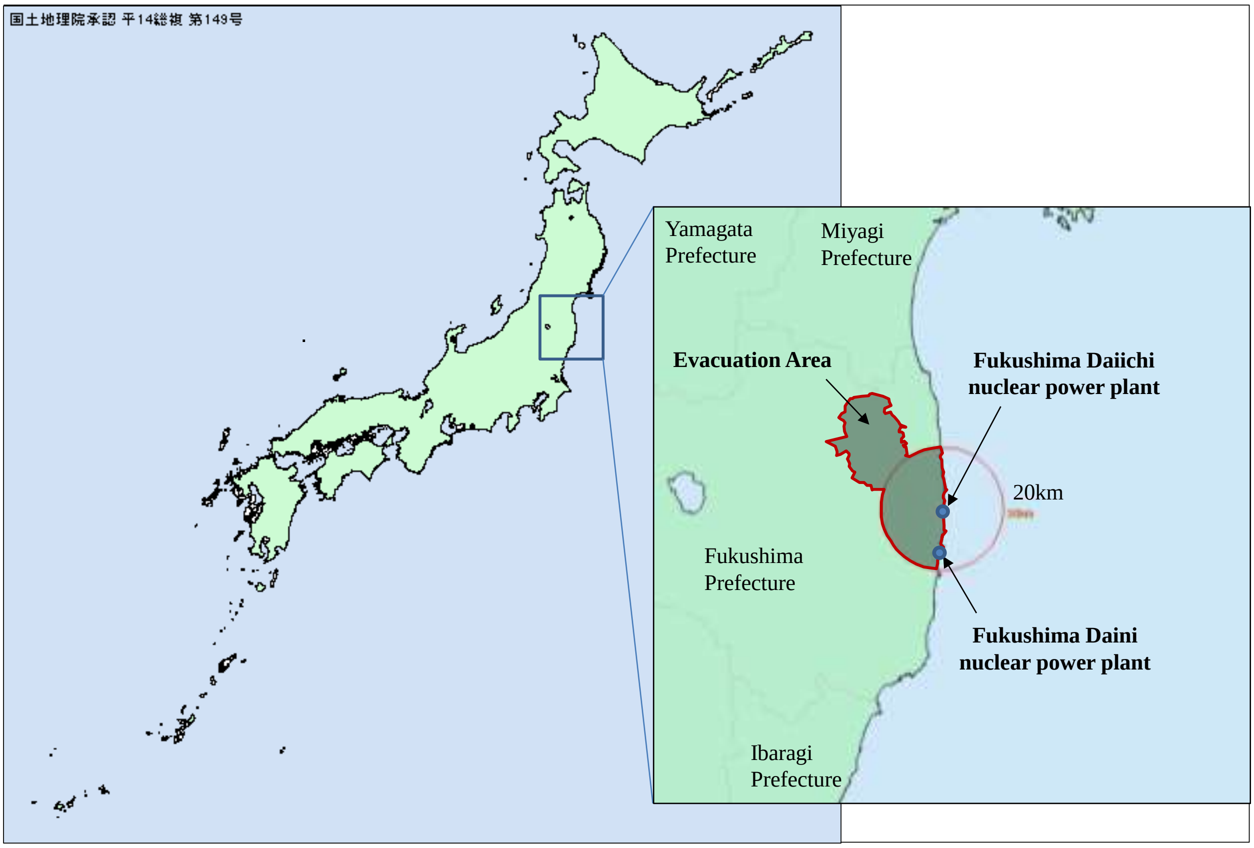
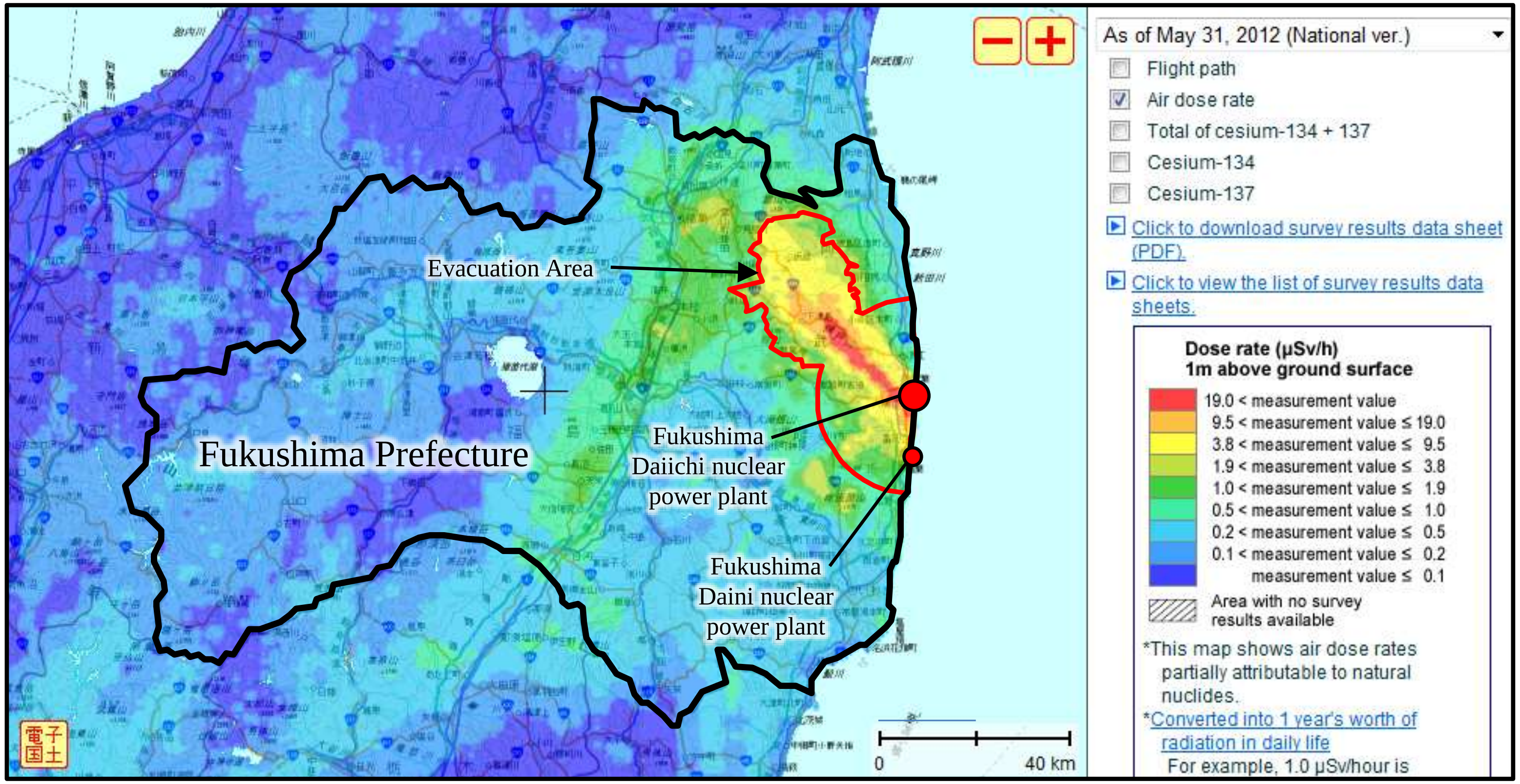


Note: This map was drawn using Kenmap, a blank map drawing software. The evacuation area consisting of the 'restricted zones' and the 'deliberate evacuation zones' is coloured dark. From April 2012, this zoning was re-examined and re-designated into five categories: (i) the conventional 'restrictive zones' which the general public is prohibited from entering, (ii) the 'deliberate evacuation zones' where evacuation is requested, (iii) zones where the return of evacuees will be difficult for a long time (the exposure dose is expected to exceed 50 mSv/year), (iv) zones where habitation is restricted (20-50 mSv/year), and (v) zones where cancelling of evacuation order is prepared (less than 20 mSv/year).

Figure 1. Location of the Fukushima Daiichi Plant



Note: This map is adapted from the *Extension Site of the Distribution Map for Radiation Dose*, a website published by the Japanese Government (http://ramap.jmc.or.jp/map/eng/). The evacuation area was not covered in the survey.

Figure 2. Objective Area and Radiation Dose Distribution (Air Dose Rate (μSv/hour))

Explanation 1: Change of the Legal Standard on Radiation Exposure Dose

Before the accident, other than natural and medical exposures, the maximum allowable radiation dose for the general public was 1 mSv/year in Japan. This standard was based on the recommendation of the International Commission on Radiological Protection (ICRP), a committee establishing international standards for radiation protection, according to which the reference levels for normal exposure situations should be set to 1 mSv/year or less.

After the accident, the legal standard was changed to 20 mSv/year or less. This change was also based on the ICRP's recommendation that reference levels for emergency exposure situations should be set in the band of 20-100 mSv/year. In April 2011, the national Nuclear Safety Commission (corresponding to the present-day Nuclear Regulation Authority) suggested the government should adopt the minimum value of the band as the maximum allowable dose for the general public.

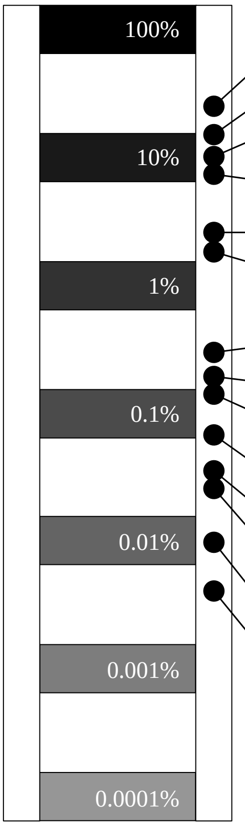
Explanation 2: Goals of Decontamination Projects

The ICRP also recommended that the reference levels for long-term post-accident situations should be set to 1-20 mSv/year. The present decontamination projects target reducing the contamination to its minimum level (1 mSv/year) as a long-term goal. In order to achieve that (i) the national government is to initiatively implement decontamination in zones where the additional exposure dose is expected to exceed 20 mSv/year, and (ii) under technical and financial support from the government, each municipality is to plan and implement decontamination in zones such that the additional exposure dose to be 1-20 mSv/year).

The above explanations cite concrete values, namely 1 or 20 mSv. Even such levels of exposure may raise the possibility of carcinogenesis. Please predict how much it rises.

Figure 3. Explanations before the Risk Perception Question

The rate and frequency of each cause of death in Japan in 2009 were as follows. Refer to this while making your prediction.



Cause of death	%	(per million deaths)
Cancer	30.12%	(301,207 deaths)
Heart disease	15.82%	(158,156 deaths)
Cerebrovascular disease	10.71%	(107,087 deaths)
Pneumonia	9.80%	(98,012 deaths)
Senility	3.38%	(33,846 deaths)
Suicide	2.68%	(26,840 deaths)
Traffic accident	0.43%	(4,297 deaths)
Tuberculosis[1]	0.20%	(2,008 deaths)
Fire accident	0.17%	(1,653 deaths)
Work-related accident	0.094%	(941 deaths)
Influenza	0.055%	(547 deaths)
Homicide	0.042%	(417 deaths)
Natural disaster[2]	0.010%	(101 deaths)
AIDS[1]	0.0056%	(56 deaths)

* Each rate was calculated on the basis of the *Demographic Statistics in Japan*, *Statistical Handbook of Japan*, *Survey on Industrial Accidents in Japan*, data of the Fire and Disaster Management Agency, and *Demographic Yearbook* (United Nations).

Note 1: The rates for tuberculosis and AIDS (Acquired Immunodeficiency Syndrome) are for 2008.

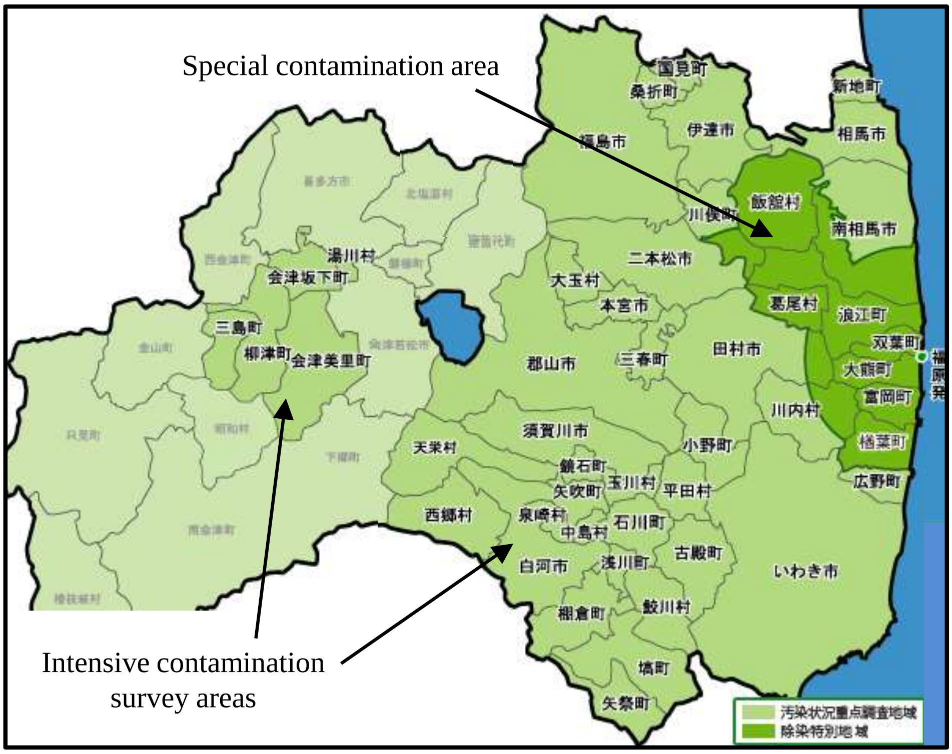
Note 2: The number of deaths by natural disaster varies greatly every year. The number in 2009 is the approximate average yearly value.

Figure 4. Risk Ladder

Q. To what extent will cancer mortalities per million people increase due to an *additional dose of 1 mSv* other than natural and medical exposures? Choose an appropriate alternative from the following list for both your lowest and highest estimates.

	Lowest estimate	Highest estimate
nobody (the rate will not rise)	1	1
more than 0 person, but 56 people or less (the same applies hereafter)	2	2
more than 56 people: *AIDS*	3	3
more than 101 people: *Natural disaster*	4	4
more than 417 people: *Homicide*	5	5
more than 547 people: *Influenza*	6	6
more than 941 people: *Work-related accident*	7	7
more than 1,653 people: *Fire accident*	8	8
more than 2,008 people: *Tuberculosis*	9	9
more than 4,297 people: *Traffic accident*	10	10
more than 26,840 people: *Suicide*	11	11
more than 33,846 people: *Senility*	12	12
more than 98,012 people: *Pneumonia*	13	13
more than 107,087 people: *Cerebrovascular disease*	14	14
more than 158,156 people: *Heart disease*	15	15
more than 301,207 people: *Cancer not caused by radioactive contamination*	16	16

Figure 5. Risk Perception Question (for an additional dose of 1 mSv)



Note: This map is adapted from the *Decontamination Information Plaza*, a website published by the Japanese Government and Fukushima Prefecture (http://josen.env.go.jp/en/). Decontamination in the special contamination area and the intensive contamination survey areas is planned and implemented by the government and the concerned municipality respectively.

Figure 6. Target Municipalities for Decontamination

Table I. Comparison with Official Statistics for the Socioeconomic Characteristics of Fukushima Residents

	This sample (n = 1,672)		Official statistics	
	Frequency	%	Frequency	%
Gender			15 years and over (n = 1,740,909)	
Male	978	(58.5)	835,901	(48.0)
Female	694	(41.5)	905,008	(52.0)
Age			15 years and over (n = 1,740,909)	
Less than 20 years old	7	(0.4)	101,390	(5.8)
20s	124	(7.4)	193,177	(11.1)
30s	425	(25.4)	249,957	(14.4)
40s	510	(30.5)	243,861	(14.0)
50s	419	(25.1)	293,886	(16.9)
60s	150	(9.0)	273,682	(15.7)
70s	35	(2.1)	221,226	(12.7)
80 years and over	2	(0.1)	163,730	(9.4)
Sample mean	45.3 years		51.7 years	
Number of household members			General households (n = 719,441)	
1 person	218	(13.0)	188,617	(26.2)
2 people	440	(26.3)	185,294	(25.8)
3 people	377	(22.5)	135,403	(18.8)
4 people	381	(22.8)	108,945	(15.1)
5 people	142	(8.5)	50,887	(7.1)
6 people	80	(4.8)	28,708	(4.0)
7 people	22	(1.3)	14,438	(2.0)
8 people	9	(0.5)	5,076	(0.7)
9 people	2	(0.1)	1,478	(0.2)
10 people or more	1	(0.1)	595	(0.1)
Sample mean	3.1 people		2.8 people	
Family income			Housholds with two or more persons (n = 890)	
x < 2 million yen	180	(10.8)	33	(3.7)
2 million ≤ x < 4 million yen	421	(25.2)	230	(25.8)
4 million ≤ x < 6 million yen	449	(26.9)	243	(27.3)
6 million ≤ x < 8 million yen	335	(20.0)	168	(18.9)
8 million ≤ x < 10 million yen	162	(9.7)	94	(10.6)
10 million ≤ x < 15 million yen	102	(6.1)	84	(9.4)
15 million ≤ x < 20 million yen	13	(0.8)	23	(2.6)
20 million yen ≤ x	10	(0.6)	15	(1.7)

Note: Official statistics for gender, age, and number of household members are sourced from the *Pupolation Census in 2010*. Official statistics for family income are sourced from the *National Survey of Family Income and Expenditure in 2009*.

Table II. Frequency Distribution of Risk Perceptions

		Cancer mortality rate raised by an additional exposure dose of 1 mSv				Cancer mortality rate raised by an additional exposure dose of 20 mSv			
Interval alternatives		Lowest prediction		Highest prediction		Lowest prediction		Highest prediction	
1.	π = 0 (nobody)	153	(18.9%)	44	(5.4%)	109	(12.6%)	28	(3.2%)
2.	0.000001 $\leq \pi \leq$ 0.000056	210	(26.0%)	131	(16.2%)	174	(20.2%)	82	(9.5%)
3.	0.000057 $\leq \pi \leq$ 0.000101	92	(11.4%)	67	(8.3%)	112	(13.0%)	79	(9.2%)
4.	0.000102 $\leq \pi \leq$ 0.000417	86	(10.6%)	96	(11.9%)	97	(11.2%)	87	(10.1%)
5.	0.000418 $\leq \pi \leq$ 0.000547	19	(2.3%)	37	(4.6%)	27	(3.1%)	42	(4.9%)
6.	0.000548 $\leq \pi \leq$ 0.000941	52	(6.4%)	48	(5.9%)	53	(6.1%)	48	(5.6%)
7.	0.000942 $\leq \pi \leq$ 0.001653	20	(2.5%)	34	(4.2%)	38	(4.4%)	37	(4.3%)
8.	0.001654 $\leq \pi \leq$ 0.002008	20	(2.5%)	26	(3.2%)	25	(2.9%)	33	(3.8%)
9.	0.002009 $\leq \pi \leq$ 0.004297	27	(3.3%)	39	(4.8%)	45	(5.2%)	47	(5.4%)
10.	0.004298 $\leq \pi \leq$ 0.026840	35	(4.3%)	61	(7.5%)	48	(5.6%)	77	(8.9%)
11.	0.026841 $\leq \pi \leq$ 0.033846	23	(2.8%)	39	(4.8%)	40	(4.6%)	57	(6.6%)
12.	0.033847 $\leq \pi \leq$ 0.098012	10	(1.2%)	20	(2.5%)	17	(2.0%)	31	(3.6%)
13.	0.098013 $\leq \pi \leq$ 0.107087	10	(1.2%)	29	(3.6%)	14	(1.6%)	45	(5.2%)
14.	0.107088 $\leq \pi \leq$ 0.158156	9	(1.1%)	34	(4.2%)	17	(2.0%)	32	(3.7%)
15.	0.158157 $\leq \pi \leq$ 0.301207	9	(1.1%)	10	(1.2%)	16	(1.9%)	22	(2.5%)
16.	0.301208 $\leq \pi \leq$ 0.698793	34	(4.2%)	94	(11.6%)	31	(3.6%)	116	(13.4%)
Total				809	(100.0%)			863	(100.0%)
Sample mean of approximate median		0.051887 (s.d. 0.120695)				0.059967 (s.d. 0.121117)			
Sample mean of approximate range		0.054317 (s.d. 0.122194)				0.066261 (s.d. 0.130128)			
(Reference) Estimated rate based on the linear no-threshold model		0.000050				0.001000			

Table III. Independent Variables

Variables	Definition	Mean		
		Total	Decon zone = 0	Decon zone = 1
Exposure dose				
d20mSv	= 1 if asked to predict the effect of 20 mSv or = 0 if 1 mSv	0.516	0.521	0.511
Images for radioactivity				
unknown	= 1 if thinking that radioactivity is an unfamiliar and mysterious thing	0.219	0.204	0.232
dread	= 1 if thinking that radioactivity is somehow a terrible thing	0.166	0.155	0.175
Perception for other health effects				
other effects	= 1 if thinking that there may be other health effects besides cancer	0.847	0.803	0.887
Socioeconomic characteristics				
decon zone	= 1 if knowing that his or her residence is located in a zone planned for decontamination, = 0 if knowing that the residence is not located there or not knowing either way	0.523	0.000	1.000
female	= 1 if female	0.415	0.419	0.412
age	age (years)	45.3	44.7	45.8
high income	= 1 if family income is 6 million yen or more	0.372	0.335	0.406
number of children	number of children aged 6 years or less (people)	0.20	0.18	0.21
Information sources				
TV/newspaper	= 1 if watcing relevant TV programs/news and reading newspaper articles	0.550	0.475	0.619
internet/SNS	= 1 if gathering with internet and social network services	0.292	0.234	0.344
neighbours	= 1 if hearing from the neighbours	0.151	0.107	0.191
magazine	= 1 if reading relevant articles of magazines	0.111	0.058	0.160
book	= 1 if reading relevant books	0.071	0.040	0.098
hearing meeting/symposium	= 1 if participating in relevant public hearing meetings and symposiums	0.070	0.040	0.097
Sample size		1,672	798	874

Note: The threshold of *high income* stems from the fact that the average family incom in Fukushima was 6.482 million yen according to the *National Survey of Family Income and Expenditure in 2009* .

Table IV. Estimation Results of Median and Range Models

	Median model						Range model					
	(1)			(2)			(1)			(2)		
Constant	-4.478	(0.335)	***	-4.639	(0.331)	***	-3.969	(0.337)	***	-4.105	(0.332)	***
Exposure dose												
d20mSv	0.242	(0.040)	***	0.257	(0.039)	***	0.222	(0.041)	***	0.240	(0.041)	***
Images for radioactivity												
unknown	0.061	(0.051)		0.097	(0.050)	**	0.094	(0.052)	*	0.137	(0.051)	***
dread	0.193	(0.058)	***	0.201	(0.057)	***	0.200	(0.058)	***	0.213	(0.057)	***
Perception for other health effects												
other effects	0.566	(0.057)	***	0.642	(0.056)	***	0.559	(0.062)	***	0.641	(0.061)	***
Socioeconomic characteristics												
decon zone	0.099	(0.041)	**	0.149	(0.040)	***	0.104	(0.043)	**	0.156	(0.041)	***
female	0.123	(0.043)	***	0.129	(0.042)	***	0.132	(0.044)	***	0.146	(0.043)	***
ln(age)	0.210	(0.085)	**	0.269	(0.084)	***	0.015	(0.087)		0.069	(0.085)	
high income	-0.304	(0.042)	***	-0.288	(0.042)	***	-0.211	(0.044)	***	-0.192	(0.043)	***
number of children	-0.001	(0.039)		0.027	(0.038)		-0.001	(0.042)		0.029	(0.041)	
Information sources												
TV/newspaper	0.187	(0.043)	***	—			0.197	(0.045)	***	—		
internet/SNS	0.222	(0.046)	***	—			0.259	(0.047)	***	—		
neighbours	0.119	(0.058)	**	—			0.248	(0.057)	***	—		
magazine	0.052	(0.070)		—			0.008	(0.072)		—		
book	-0.107	(0.085)		—			-0.165	(0.090)	*	—		
hearing meeting/symposium	0.023	(0.079)		—			-0.069	(0.087)		—		
Log likelihood	-4771.1			-4792.0			-3613.6			-3640.3		
Sample size	1,672											

Note: Standard errors are shown in parentheses. ***, **, and *: significant at 1%, 5%, and 10% respectively.

Table V. Correlations between Information and Other Variables

	unknown	dread	other effects	decon zone	female	age	high income	number of children
TV/newspaper	0.1123	0.0245	0.1932	0.1446	0.0589	0.0724	0.0435	0.0720
internet/SNS	0.0451	0.0395	0.0903	0.1209	-0.0549	0.0117	0.0148	0.0458
neighbours	0.1004	0.0731	0.1048	0.1181	0.0726	0.0008	0.0364	0.0964
magazine	0.0979	0.0009	0.0870	0.1629	-0.0471	0.0723	0.0488	-0.0177
book	0.0123	-0.0223	0.0523	0.1137	-0.0189	0.0022	0.0429	0.0585
hearing meeting/symposium	0.0135	-0.0150	0.0255	0.1119	-0.0265	0.1069	0.0802	0.0458