

Can radiation-contaminated food be marketed?*

Makoto SAITO[†] Masataka SUZUKI

November 2011

Abstract

This paper presents a simple theoretical model to explain consistently heterogeneous patterns in consumers' valuation on radiation-contaminated milk by explicitly incorporating a strong preference for zero radiation risks. In particular, it establishes a rigorous condition under which contaminated milk is still traded at discount prices even when contamination levels are relatively high. Using an internet-based questionnaire survey consisting of 7,600 respondents, we empirically explore whether the above condition holds. According to estimation results, as milk contains more radiation, a contaminated milk market disappears quickly among those who originally perceive their own cancer risks to be rather low. Conversely, contaminated milk is still traded at discount prices among those who are regarded as having already carried considerable cancer risks.

*The authors would like to thank Tao Gu, Kyosuke Haseyama, and Teruyuki Sakaue for excellent research assistance, and acknowledge Makoto Nirei, and seminar participants at Hitotsubashi University for their helpful comments. The authors are grateful for a grant-in-aid from the Ministry of Education and Science, Japan.

[†]Correspondence to: Makoto SAITO, Faculty of Economics, Hitotsubashi University, 2-1, Naka, Kunitachi, Tokyo, 186-8601, Japan, E-mail: makoto@econ.hit-u.ac.jp, phone: +81-42-580-8807, fax: +81-42-580-8882.

1 Motivation

Many kinds of food were contaminated by radiation which was released from the explosion at the Fukushima No. 1 nuclear plant in March 2011. Some of such radiation-contaminated food immediately lost market liquidity even if they satisfied safety standards. Many researchers, including economists, interpreted such phenomena as heavily driven by groundless and unscientific rumors, and as a consequence of irrational excessive reaction to slight radiation possibility.

However, a particular consumer may be acutely sensitive to a possibility that food is contaminated by slight radiation. Given such a strong aversion to low-level radiation risks, his/her extreme reluctance to purchase slightly contaminated food can be interpreted as not irrational adverse reaction, but rational proper response. Thus, it may not be interesting for us to ask ourselves whether a particular consumer's reaction to radiation-contaminated food is irrational or rational.

A more appealing question may be whether consumers' attitudes toward radiation risks are heterogeneous enough to sustain market liquidity for contaminated food. If there emerges a market in which contaminated food is discounted to the extent that food is contaminated, by risk-generous consumers, then shrinking demand among keenly risk-averse consumers is replaced to some extent by steady demand from relatively risk-generous consumers. We call such a discount transaction a 'secondary' market as opposed to a 'primary' market in which food, considered as harmless, is traded without any discount for radiation risks.

We usually interpret taking radiation risks by eating radiation-contaminated food as taking additional cancer risks. According to the prospect theory, those who originally perceive their own cancer risks to be rather low tend to overreact to additional cancer risks, while those who are regarded as having already carried considerable cancer risks are likely to be insensitive to a tiny increase in cancer risks. In other words, the former (latter) type of consumers demonstrates a strong (weak) preference for zero cancer risks.

In this paper, we present a simple theoretical model to explain consistently heterogeneous patterns in consumers' valuation on radiation-contaminated food by explicitly incorporating varying degrees of preferences for zero radiation risks. For this purpose, we construct as a structural model, a discrete/continuous choice model from a set of sim-

ple assumptions of idiosyncratic preference shocks. From this simple theoretical model, we can analytically derive, given a contamination level, how many consumers purchase radiation-contaminated milk at a primary market, how many discount it at a secondary market, and how many reveal a refusal to buy it. In addition, this model yields an analytical form of a density function for prices quoted by those who discount contaminated milk. Consequently, we can define statistical likelihood functions rigorously, and estimate this model by the maximum likelihood estimator.

As reasonably expected, both primary and secondary markets shrink rather quickly among those who reveal a strong preference for zero radiation risks. Conversely, a secondary market is expected to be active among those whose preference for zero risks is fairly weak. In the above model, we theoretically explore when active secondary markets are substituted for disappearing primary markets, and when even secondary markets disappear rather quickly. If the former is a case, then a market mechanism works to some extent to sustain liquidity for contaminated food markets.

Taking radiation-contaminated milk for example, we conducted an internet-based questionnaire survey consisting of 7,600 consumers who were living in the Tokyo metropolitan area in August 2011. We provided each respondent with a brief description about how safety standards are set officially for radiation-contaminated milk. That is, following the instruction issued by the International Commission on Radiological Protection (ICRP), the Japanese government set 200 Becquerel (Bq) of cesium per kilogram of milk as the upper limit, thereby reducing radiation-driven cancer risks to extremely low levels.

We then asked them how they responded to milk contaminated at a level of 10 Bq per kilogram, 50 Bq/kg, 100 Bq/kg, and 200 Bq/kg (corresponding to the upper limit). Each responded by either purchasing it at a normal price (set at 200 yen per one liter pack), discounting it below 200 yen, or refusing to purchase it at any price. We also conducted a survey on the characteristics of the respondents, including their perception about own cancer risks.

According to our estimation results, there are consumers whose degree of zero risk preferences is on either side of the critical value below which a secondary market partially substitutes for a primary market. More concretely, those who originally perceive their own cancer risks to be rather low are unlikely to purchase contaminated milk at even heavily discount prices. Conversely, those who are regarded as having already carried considerable cancer risks, including heavy smokers and regular drinkers, are rel-

actively generous to radiation-contaminated milk. Thus, there is still a possibility that a secondary market works for such risk-generous consumers.

(to be completed)

2 A simple theoretical model

2.1 A basic setup

2.1.1 A case with/without a threshold

In this section, we construct as a structural form, a discrete/continuous choice model to explain heterogeneous patterns in consumers' valuation about radiation-contaminated milk. We below formalize how the valuation of contaminated milk decreases with a contamination level.

Suppose that one liter pack of milk is usually sold at 200 yen, and that it is evaluated at v_i by consumer i when it is possibly contaminated by radiation. As mentioned in the introduction, the upper limit of a contamination level was set at 200 Bq of cesium per kilogram for milk by the government. We thus consider several cases in which milk is contaminated at D Bq per kilogram, where $0 < D \leq 200$.

Suppose that consumer i evaluates one liter pack of radiation-contaminated milk according to the following equation:

$$v_i = -p_i d_i + 200(1 - p_i), \quad (1)$$

where p_i represents a subjective evaluation about the probability that cancer risks are realized, and d_i denotes a subjective assessment of a damage which would result from the realization of cancer risks. As equation (1) implies, the valuation of contaminated milk decreases with p_i . We here define \hat{p}_i as the physical upper limit of p_i where $0 = -\hat{p}_i d_i + 200(1 - \hat{p}_i)$.

We consider cases with/without a threshold point. In a case without any threshold, $v_i = 200$ if $p_i = 0$, $0 < v_i < 200$ if $\hat{p}_i > p_i > 0$, and $v_i = 0$ if $p_i = \hat{p}_i$. As depicted in Figure 1-1, the first (second, or third) case is called a case where a radiation risk is considered as *harmless* (*tolerable*, or *intolerable*).

In a case with a threshold, consumer i lowers the admissible upper limit of p_i from \hat{p}_i to \bar{p}_i . We here define \underline{v}_i as the lower limit of v_i where $\underline{v}_i = -\bar{p}_i d_i + 200(1 - \bar{p}_i)$. As

shown in Figure 1-2, the valuation of contaminated milk (v_i) jumps from \underline{v}_i to zero once a radiation risk reaches \bar{p}_i in terms of probability.

Here, we interpret $\frac{\hat{p}_i}{\bar{p}_i}$ as a risk-adjusted weight for the probability that an *intolerable* cancer risk is realized. Once \underline{v}_i is available, we obtain the above risk-adjusted weight as follows:

$$\frac{\hat{p}_i}{\bar{p}_i} = \frac{200}{200 - \underline{v}_i}. \quad (2)$$

In the estimation procedure, we indeed estimate \underline{v}_i .

2.1.2 Introducing idiosyncratic shocks

We below model the above individual valuation of radiation-contaminated milk by introducing a set of idiosyncratic shocks. Because definite opinions about the potential impact of radiation contamination may not be formed among consumers, we here formulate idiosyncratic shocks such that there emerge large degrees of heterogeneity in risk attitudes even among observationally equivalent consumers.

As described above, when a radiation risk is regarded as *harmless*, a consumer purchases one liter pack of contaminated milk at a normal price or 200 yen. That is, $v_i = 200$. On the other hand, a consumer does not purchase contaminated milk at any price when a radiation risk is regarded as *intolerable*. Consequently, $v_i = 0$. As an intermediate case where a radiation risk is *tolerable*, a consumer purchases contaminated milk, but discounts it. Accordingly, $0 < v_i < 200$ in a case without any threshold, and $\underline{v}_i < v_i < 200$ in a case with a threshold.

The above three cases are modeled as follows. The valuation v_i revealed by consumer i is characterized by two random variables, x and y , as idiosyncratic shocks. Here, x is uniformly distributed between \underline{D}_i (≤ 0) and \bar{D}_i (≥ 200), while given $x = X$, y is uniformly distributed between X and \bar{D}_i . That is,

$$x \sim U [\underline{D}_i, \bar{D}_i], \quad (3)$$

$$y|_{x=X} \sim U [X, \bar{D}_i], \quad (4)$$

where $U[.,.]$ denotes the uniform distribution operator.

Figure 2 depicts a valuation function where v_i is decreasing with D in a situation where y is drawn from the uniform distribution given $x = X$. In **Case 1**, the consumer's valuation (v_i) is equal to 200 yen when the contamination level (D) is lower than X (see

Figure 3-1). In **Case 2**, v_i is between \underline{v}_i (≥ 0) and 200 yen when $X \leq D \leq y$ (see Figure 3-2). Here, the consumer's valuation (v_i) is assumed to decrease linearly with D as long as D is below y , but v jumps from \underline{v}_i to zero at $D = y$ in the presence of a threshold \underline{v}_i . In **Case 3**, v_i is equal to zero when $D > y$ (see Figure 3-3).

\underline{D}_i , \overline{D}_i , and \underline{v}_i jointly parameterize the consumer's attitude toward radiation risks. More concretely, lower \underline{D}_i implies stronger preference for zero risks, when \overline{D}_i is given at \overline{D} (> 200). As discussed before, on the other hand, larger \underline{v}_i indicates a lower admissible upper limit of the probability that a radiation risk is realized.

2.2 Computing the unconditional probability of the three cases

We below compute the unconditional probability that each of the three cases takes place. From now on, we assume \overline{D}_i to be set at \overline{D} (> 200) for all consumers, thereby interpreting the value of \underline{D}_i relative to \overline{D} as the degree of a preference for zero radiation risks.

In Case 1, $v_i = 200$ when $D < X$. Thus, how Case 1 is likely to occur corresponds to the probability that x is between D and \overline{D} .

$$\begin{aligned} \Pr(D \leq x) &= \int_D^{\overline{D}} \frac{1}{\overline{D} - \underline{D}_i} dx \\ &= \frac{\overline{D} - D}{\overline{D} - \underline{D}_i}. \end{aligned} \quad (5)$$

In Case 2, $\underline{v}_i < v_i < 200$ when D is between x and y . The conditional probability that $X < D < y$ given $x = X$ is computed as follows:

$$\begin{aligned} \Pr(D < y | x = X) &= \int_D^{\overline{D}} \frac{1}{\overline{D} - X} dy \\ &= \frac{\overline{D} - D}{\overline{D} - X}. \end{aligned} \quad (6)$$

Thus, the unconditional probability for Case 2 is computed by integrating equation (6) over $\underline{D}_i < x < D$:

$$\begin{aligned} \Pr(x < D < y) &= \int_{\underline{D}_i}^D \left(\frac{\overline{D} - D}{\overline{D} - x} \frac{1}{\overline{D} - \underline{D}_i} \right) dx \\ &= \frac{\overline{D} - D}{\overline{D} - \underline{D}_i} [\ln(\overline{D} - \underline{D}_i) - \ln(\overline{D} - D)]. \end{aligned} \quad (7)$$

In Case 3, $v_i = 0$ when $y \leq D$. The conditional probability of Case 3 given $x = X$ is computed as follows:

$$\begin{aligned}\Pr(y \leq D | x = X) &= 1 - \Pr(D < y | x = X) \\ &= \frac{D - X}{\bar{D} - X}.\end{aligned}\quad (8)$$

By integrating equation (8) over $\underline{D}_i < x < D$, the unconditional probability of Case 3 is computed as below:

$$\begin{aligned}\Pr(y \leq D) &= \int_{\underline{D}_i}^D \left(\frac{D - x}{\bar{D} - x} \frac{1}{\bar{D} - \underline{D}_i} \right) dx \\ &= \frac{D - \underline{D}_i}{\bar{D} - \underline{D}_i} - \frac{\bar{D} - D}{\bar{D} - \underline{D}_i} [\ln(\bar{D} - \underline{D}_i) - \ln(\bar{D} - D)].\end{aligned}\quad (9)$$

From equations (5), (7) and (9), we have $\Pr(D \leq x) + \Pr(x < D < y) + \Pr(y \leq D) = 1$.

2.3 Derivation of the conditional density function of v for Case 2

2.3.1 The conditional density function

In Case 2, consumers purchase radiation-contaminated milk, but discount it when a contamination level is tolerable. More concretely, $0 \leq \underline{v}_i < v_i < 200$ when $X < D < y$ given $x = X$. As described before, the valuation function is linear with a discontinuous valuation point where v_i jumps from \underline{v}_i to zero at $D = y$. Note that $\underline{v}_i = 0$ in a case without any threshold.

Thus, the function of v_i for Case 2 is formulated as follows:

$$v_i(y | x = X) = 200 - \frac{200 - \underline{v}_i}{y - X} (D - X). \quad (10)$$

Using a change of random variable technique, we below derive the conditional density function for v_i given $X < D < y$ from equations (4) and (10).

$$\varphi(v_i(y) | X < D < y) = \frac{(200 - \underline{v}_i)(D - X)}{(\bar{D} - D)(200 - v_i)^2}. \quad (11)$$

Given v_i , the lower limit of x is $D_l(v) \equiv \max\left\{\underline{D}_i, D - \frac{200 - v_i}{v_i - \underline{v}_i} (\bar{D} - D)\right\}$. Then, by integrating over x , the conditional density function for v_i given $x = X < D < y$ is

derived as follows:

$$\begin{aligned}
\varphi(v_i(y)|x < D < y) &= \int_{D_l(v)}^D \frac{(200 - \underline{v}_i)(D - x)}{(\bar{D} - D)(200 - v_i)^2} \left(\frac{1}{D - \underline{D}_i} \right) dx \\
&= \frac{(200 - \underline{v}_i)}{2(\bar{D} - D)(D - \underline{D}_i)(200 - v_i)^2} \{D - D_l(v)\}^2 \\
&= \begin{cases} \frac{(200 - \underline{v}_i)(D - \underline{D}_i)}{2(\bar{D} - D)(200 - v_i)^2}, & \underline{v}_i \leq v_i < \hat{v}_i \\ \frac{(200 - \underline{v}_i)(\bar{D} - D)}{2(D - \underline{D}_i)(v_i - \underline{v}_i)^2}, & \hat{v}_i \leq v_i < 200, \end{cases} \quad (12)
\end{aligned}$$

where:

$$\hat{v}_i = \underline{v}_i + (200 - \underline{v}_i) \frac{\bar{D} - D}{\bar{D} - \underline{D}_i}. \quad (13)$$

2.3.2 Some statistics of the conditional distribution of v

As the appendix proves, the above-derived conditional density function of v yields the identical median and mode at $\hat{v}_i = \underline{v}_i + (200 - \underline{v}_i) \frac{\bar{D} - D}{\bar{D} - \underline{D}_i}$.

On the other hand, the conditional expectation of v is calculated as follows:

$$\begin{aligned}
E[v_i|x < D < y] &= \int_{\underline{v}_i}^{200} v_i \cdot \varphi(v_i(y)|x < D < y) dv \\
&= \int_{\underline{v}_i}^{\hat{v}_i} \frac{v_i(200 - \underline{v}_i)(D - \underline{D}_i)}{2(\bar{D} - D)(200 - v_i)^2} dv + \int_{\hat{v}_i}^{200} \frac{v(200 - \underline{v}_i)(\bar{D} - D)}{2(D - \underline{D}_i)(v_i - \underline{v}_i)^2} dv \\
&= \frac{200 + \underline{v}_i}{2} + \frac{200 - \underline{v}_i}{2} \left[\frac{D - \underline{D}_i}{\bar{D} - D} \ln \left(\frac{D - \underline{D}_i}{\bar{D} - \underline{D}_i} \right) - \frac{\bar{D} - D}{D - \underline{D}_i} \ln \left(\frac{\bar{D} - D}{\bar{D} - \underline{D}_i} \right) \right]. \quad (14)
\end{aligned}$$

We below present some properties of the above statistics. As reasonably expected, a consumer discounts contaminated milk heavily as a contamination level (D) increases. Thus, the mode (identical to the median) and the conditional average is expected to be decreasing in D .

The mode (median) of v_i , equal to \hat{v}_i , indeed decreases as D increases.

$$\frac{\partial \hat{v}_i}{\partial D} = - \left(\frac{200 - \underline{v}_i}{\bar{D} - \underline{D}_i} \right) \leq 0. \quad (15)$$

As shown below, the conditional expectation of v is also decreasing in D :

$$\begin{aligned}
\frac{\partial E[v_i | x < D < y]}{\partial D} &= \frac{200 - v_i}{2} \left[\frac{\bar{D} - \underline{D}_i}{(\bar{D} - D)^2} \ln \left(\frac{D - \underline{D}_i}{\bar{D} - \underline{D}_i} \right) + \frac{\bar{D} - \underline{D}_i}{(D - \underline{D}_i)^2} \ln \left(\frac{\bar{D} - D}{\bar{D} - \underline{D}_i} \right) + \frac{\bar{D} - \underline{D}_i}{(\bar{D} - D)(D - \underline{D}_i)} \right] \\
&\leq \frac{200 - v_i}{2} \left[\frac{\bar{D} - \underline{D}_i}{(\bar{D} - D)^2} \left(\frac{D - \bar{D}}{\bar{D} - \underline{D}_i} \right) + \frac{\bar{D} - \underline{D}_i}{(D - \underline{D}_i)^2} \left(\frac{\underline{D}_i - D}{\bar{D} - \underline{D}_i} \right) + \frac{\bar{D} - \underline{D}_i}{(\bar{D} - D)(D - \underline{D}_i)} \right] \\
&= 0,
\end{aligned} \tag{16}$$

where we use the inequality $\ln x \leq x - 1$ in the second line of equation (16).

A consumer with lower \underline{D}_i relative to \bar{D} is more sensitive to radiation risks, and discounts contaminated milk more heavily. It is easy to show that both the mode (or the median, \hat{v}) and the conditional expectation ($E[v | x < D < y]$) is increasing in both \underline{D}_i and v_i .

2.4 A possibility that secondary markets substitute for primary markets

In this subsection, we explore whether secondary markets (Case 2) may substitute for primary markets (Case 1) as contamination becomes serious, thereby preventing markets for contaminated milk from disappearing quickly (Case 3). That is, we examine whether consumers trade contaminated milk actively at discount prices, even when a contamination level increases.

As shown below, the unconditional probability that Case 1 emerges is monotonically decreasing in a contamination level (D).

$$\frac{\partial \Pr(v_i = 200)}{\partial D} = -\frac{1}{\bar{D} - \underline{D}_i} < 0. \tag{17}$$

On the other hand, the unconditional probability that Case 3 emerges is monotonically increasing in D .

$$\frac{\partial \Pr(v_i = 0)}{\partial D} = \frac{1}{\bar{D} - \underline{D}_i} \ln \left(\frac{\bar{D} - \underline{D}_i}{\bar{D} - D} \right) > 0. \tag{18}$$

Consequently, how the probability that Case 2 behaves as contamination levels increase depends on whether a decrease in the probability of Case 1 is dominated by an increase in the probability of Case 3.

From equation (7), the partial derivative of $\Pr(0 < v_i < 200)$ with respect to D is

calculated as follows:

$$\frac{\partial \Pr(0 < v_i < 200)}{\partial D} = \frac{1}{\bar{D} - \underline{D}_i} \left(1 + \ln \frac{\bar{D} - D}{\bar{D} - \underline{D}_i} \right). \quad (19)$$

From equation (19), if $D \leq \underline{D}_i + (\bar{D} - \underline{D}_i) \left(1 - \frac{1}{\exp(1)} \right)$, then $\frac{\partial \Pr(0 < v < 200)}{\partial D} \geq 0$. Hence, if $\frac{-\underline{D}_i}{\bar{D} - \underline{D}_i} \leq 1 - \frac{1}{\exp(1)} \approx 0.632$, $\frac{\partial \Pr(0 < v < 200)}{\partial D}$ can be positive when D is positive.¹ In this case, a secondary market substitutes to some extent for a primary market, before both markets shrink.

On the other hand, if $\frac{-\underline{D}_i}{\bar{D} - \underline{D}_i} > 1 - \frac{1}{\exp(1)} \approx 0.632$, then $\frac{\partial \Pr(0 < v < 200)}{\partial D}$ is always negative. In this case, an increase in contamination levels necessarily dampens demand in a secondary market where radiation-contaminated milk is discounted continuously according to the contamination level.

As the above argument suggests, $\kappa_i \equiv \frac{-\underline{D}_i}{\bar{D} - \underline{D}_i}$ can be interpreted as a key parameter about the degree of zero risk preferences. As discussed before, the absolute value of \underline{D}_i represents how strong a preference for zero radiation risks is. Thus, as a preference for zero radiation risks is weaker, $|\underline{D}_i|$ is smaller, and κ_i is lower. Thus, to the extent that a preference for zero radiation risks is weak, a secondary market can be substituted for a primary market.

Our empirical interest lies in how high κ_i is for a consumer with particular characteristics. We want to infer from the estimated value of κ_i how milk markets are robust (or fragile) with respect to radiation contamination.

¹ $1 - \frac{1}{\exp(1)} \approx 0.632$ has the following interesting interpretation. Choose the population size q where a rare catastrophic event with occurrence probability $1/q$ hits averagely on one person in the population. Then, the probability that at least one person is hit by this rare event is computed as

$$1 - \lim_{q \rightarrow \infty} (1 - 1/q)^q = 1 - \frac{1}{\exp(1)}.$$

The fact that at least one person living in a society suffers from cancer due to radiation may trigger an extremely adverse impact on a market transaction of contaminated food. In this sense, we may claim that a market of contaminated food breaks down with probability of 0.632, when a substantial portion of consumers in a society are extremely attentive to the realization of such infrequent events. On the other hand, κ_i represents the probability that x is negative for consumer i . Thus, κ_i is interpreted as the probability that consumer i has a strong preference for zero risks. Therefore, our proposition can be interpreted as follows: if a consumer turns out to be keenly averse to such a rare catastrophic event with probability of 63.2%, then a secondary market of contaminated food indeed fails to work effectively with probability of 63.2%.

2.4.1 Some numerical examples

As discussed above, $\kappa_i (= \frac{-D_i}{D-D_i})$ plays a key role in determining how the probability of Case 2 behaves. If κ_i is greater than $1 - \frac{1}{\exp(1)}$ (≈ 0.632), then primary and secondary markets shrink simultaneously as D increases.

Figures 4-1 through 4-3 depict how the unconditional probability of each of the three cases changes as contamination levels change. Figure 4-1 (4-2, 4-3) assumes that κ_i is equal to 0.038 (0.167, 0.688). Since $\kappa_i < 0.632$ in the first two figures, the probability of Case 2 is increasing in D unless D is fairly high. In these cases, secondary markets are somewhat robust with respect to radiation contamination. In the last figure, however, κ_i is greater than 0.632, and the probability of Case 2 is monotonically decreasing in D . That is, primary and secondary markets shrink simultaneously in response to more radiation-contaminated milk.

The above key parameter κ_i also plays a significant role in determining the shape of the density functions for Case 2. As demonstrated in Figures 5-1 ($\kappa_i = 0.4$) and 5-2 ($\kappa_i = 0.25$), the mode (equivalently the median) of the density function shifts more downward in response to an increase in D when κ_i is large.

3 A statistical model

In this section, we present a statistical model by introducing a linear specification into the two systematic parts (\underline{D}_i and \underline{v}_i) in the discrete/continuous choice model of the previous section. We thus define logarithmic likelihood functions depending on how a consumer evaluate one liter pack of milk contaminated at D . With such preparation, we estimate a set of structural parameters by the maximum likelihood estimation.

One potential complication here is that we may observe the individual valuation of milk not at a single, but multiple contamination levels. In the questionnaire survey conducted in this study, we indeed asked each respondent about his/her valuation of milk contaminated at four levels, that is, 10 Bq, 50 Bq, 100 Bq, and 200 Bq.

In this section, we thus propose a statistical model first for a case with a single contamination level, and then move to a case with multiple contamination levels.

3.1 A case where the individual valuation is observed at a single contamination level

In our theoretical model, there are three consumer-specific parameters $\Theta \equiv (\bar{D}, \underline{D}_i, v_i)$ that determine how an individual consumer responds to radiation risks. We expect that \underline{D}_i and v_i are systemically correlated with individual characteristics such as gender, age, income level, and so on. Given such systematic parts, the random variables x and y can be interpreted as idiosyncratic preference shocks.

We thus assume the following linear specification for these systemic parts:

$$\underline{D}_i = \mathbf{z}_i \beta + \text{const}_{\underline{D}}, \quad (20)$$

$$v_i = \mathbf{z}_i \gamma + \text{const}_v, \quad (21)$$

where \mathbf{z}_i is a $1 \times K$ vector which represents individual characteristics, and β and γ are respectively $K \times 1$ coefficient vectors.

It is in principle possible to formulate $\bar{D}_i = \mathbf{z}_i \alpha + \text{const}_{\bar{D}}$ as well. But, we treat \bar{D} as a constant parameter to avoid potential identification problems in estimating \bar{D}_i together with \underline{D}_i and v_i .

Given the individual valuation (v_i) of milk contaminated at D , we derive from equation (5), (7), (9), and (12), the following logarithmic likelihood functions:

$$\ln L(v | \Theta, D) = \begin{cases} \ln \left[\frac{D - \underline{D}_i}{\bar{D} - \underline{D}_i} - \frac{\bar{D} - D}{\bar{D} - \underline{D}_i} \{ \ln(\bar{D} - \underline{D}_i) - \ln(\bar{D} - D) \} \right], & v_i = 0 \\ \ln \left[\frac{(200 - v_i)(D - \underline{D}_i)}{2(\bar{D} - \underline{D}_i)(200 - v_i)^2} \{ \ln(\bar{D} - \underline{D}_i) - \ln(\bar{D} - D) \} \right], & \underline{v}_i \leq v_i < \hat{v} \\ \ln \left[\frac{(200 - v_i)(\bar{D} - D)^2}{2(\bar{D} - \underline{D}_i)(D - \underline{D}_i)(v_i - \underline{v}_i)^2} \{ \ln(\bar{D} - \underline{D}_i) - \ln(\bar{D} - D) \} \right], & \hat{v} \leq v_i < 200 \\ \ln \left[\frac{\bar{D} - D}{\bar{D} - \underline{D}_i} \right], & v_i = 200. \end{cases} \quad (22)$$

From equations (20) through (22), we can estimate coefficients (β, γ) by the maximum likelihood estimation. In this case, \bar{D} cannot be pinned down without any information about a slope of linear valuation through two or more observations included in Case 2. Thus, \bar{D} must be predetermined.

3.2 A case where the individual valuation is observed at multiple contamination levels

In this subsection, we consider a case where the individual valuation of contaminated milk is observed at not a single level D , but multiple levels D^j where $j = 1, 2, 3$, and 4. With more observations of the individual valuation, we can pin down more specifically the range of two random variables x and y , thereby narrowing the range of integration in deriving distribution (density) functions.

More concretely, we narrow the range of these random variables as follows. If Case 1 is observed for D^j , then the lower limit of x is not \underline{D}_i , but D^j . If Case 2 is observed for D^j , then the upper limit of x is not \overline{D} , but D^j , and the lower limit of y is not \underline{D}_i , but D^j . If Case 3 is observed for D^j , then the upper limit of y is D^j .

When there are two or more observations in Case 2, the range of the valuation v_i is narrowed as well. Taking a case with two observations at both D^2 and D^3 included in Case 2 for example, as shown in Figure 6-1, the upper limit of x reduces to D^2 when a threshold is absent ($\underline{v}_i = 0$). Consequently, the upper limit of v_i at D^3 becomes low relative to 200 yen. As depicted in Figure 6-2, on the other hand, the lower limit of y increases to D^3 . As a result, the lower limit of v_i at D^2 becomes high relative to zero yen. The above argument suggests that \overline{D} can be estimated from the information about the distribution of discount prices, which are observed in Case 2.

In the presence of a threshold ($\underline{v}_i > 0$), the upper limit of v_i is relaxed to some extent. As shown in Figure 6-1, it increases from (a) to (b) at D^3 . On the other hand, the lower limit of v_i is restricted more with $\underline{v}_i > 0$. As shown in Figure 6-2, it increases from (a) to (b) at D^2 .

Taking the above aspects into consideration, we below derive a set of logarithmic likelihood functions in a case where the individual valuation of contaminated milk is observed at multiple contamination levels D^j for $j = 1, 2, 3, 4$. In our questionnaire survey, $(D^1, D^2, D^3, D^4) = (10, 50, 100, 200)$. For each D^j , the valuation of radiation-contaminated milk by consumer i is denoted by v_i^j .

To simplify the notation, we define as follows **Case** $\equiv (k^1, k^2, k^3, k^4)$ where $k^j = 1, 2, 3$. Each k^j represents one of the three cases when a contamination level is D^j . For example, if the valuation of contaminated milk by consumer i is observed as $v_i^1 = v_i^2 = 200$, $\underline{v}_i < v_i^3 < 200$, and $v_i^4 = 0$, then **Case** $= (1, 1, 2, 3)$.

By construction, v_i^j is non-increasing in D^j . Consequently, there are fifteen combina-

tions in **Case**: $(k^1, k^2, k^3, k^4) = (1, 1, 1, 1), (1, 1, 1, 2), (1, 1, 1, 3), (1, 1, 2, 2), (1, 1, 2, 3), (1, 1, 3, 3), (1, 2, 2, 2), (1, 2, 2, 3), (1, 2, 3, 3), (1, 3, 3, 3), (2, 2, 2, 2), (2, 2, 2, 3), (2, 2, 3, 3), (2, 3, 3, 3),$ and $(3, 3, 3, 3)$.

Then, the unconditional probability of each combination is derived as follows:

$$\begin{aligned}
& \Pr(\text{case}) \\
& = \begin{cases} \Pr(D^4 \leq x) = \frac{\bar{D}_i - D^4}{\bar{D}_i - \underline{D}_i}, & \text{Case} = (1, 1, 1, 1) \\ \Pr(D^3 \leq x < D^4 < y) = \frac{\bar{D}_i - D^4}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - D^3}{\bar{D}_i - D^4} \right), & \text{Case} = (1, 1, 1, 2) \\ \Pr(D^3 \leq x \leq y \leq D^4) = \frac{1}{\bar{D}_i - \underline{D}_i} \left[(D^4 - D^3) - (\bar{D}_i - D^4) \ln \left(\frac{\bar{D}_i - D^3}{\bar{D}_i - D^4} \right) \right], & \text{Case} = (1, 1, 1, 3) \\ \Pr(D^2 \leq x < D^3 < D^4 < y) = \frac{\bar{D}_i - D^4}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - D^2}{\bar{D}_i - D^3} \right), & \text{Case} = (1, 1, 2, 2) \\ \Pr(D^2 \leq x < D^3 < y \leq D^4) = \frac{D^4 - D^3}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - D^2}{\bar{D}_i - D^3} \right), & \text{Case} = (1, 1, 2, 3) \\ \Pr(D^2 \leq x \leq y \leq D^3) = \frac{1}{\bar{D}_i - \underline{D}_i} \left[(D^3 - D^2) - (\bar{D}_i - D^3) \ln \left(\frac{\bar{D}_i - D^2}{\bar{D}_i - D^3} \right) \right], & \text{Case} = (1, 1, 3, 3) \\ \Pr(D^1 \leq x < D^2 < D^4 < y) = \frac{\bar{D}_i - D^4}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - D^1}{\bar{D}_i - D^2} \right), & \text{Case} = (1, 2, 2, 2) \\ \Pr(D^1 \leq x < D^2 < D^3 < y \leq D^4) = \frac{D^4 - D^3}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - D^1}{\bar{D}_i - D^2} \right), & \text{Case} = (1, 2, 2, 3) \\ \Pr(D^1 \leq x < D^2 < y \leq D^3) = \frac{D^3 - D^2}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - D^1}{\bar{D}_i - D^2} \right), & \text{Case} = (1, 2, 3, 3) \\ \Pr(D^1 \leq x \leq y \leq D^2) = \frac{1}{\bar{D}_i - \underline{D}_i} \left[(D^2 - D^1) - (\bar{D}_i - D^2) \ln \left(\frac{\bar{D}_i - D^1}{\bar{D}_i - D^2} \right) \right], & \text{Case} = (1, 3, 3, 3) \\ \Pr(x < D^1 < D^4 < y) = \frac{\bar{D}_i - D^4}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - \underline{D}_i}{\bar{D}_i - D^1} \right), & \text{Case} = (2, 2, 2, 2) \\ \Pr(x < D^1 < D^3 < y \leq D^4) = \frac{D^4 - D^3}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - \underline{D}_i}{\bar{D}_i - D^1} \right), & \text{Case} = (2, 2, 2, 3) \\ \Pr(x < D^1 < D^2 < y \leq D^3) = \frac{D^3 - D^2}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - \underline{D}_i}{\bar{D}_i - D^1} \right), & \text{Case} = (2, 2, 3, 3) \\ \Pr(x < D^1 < y \leq D^2) = \frac{D^2 - D^1}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - \underline{D}_i}{\bar{D}_i - D^1} \right), & \text{Case} = (2, 3, 3, 3) \\ \Pr(y \leq D^1) = \frac{D^1 - \underline{D}_i}{\bar{D}_i - \underline{D}_i} - \frac{\bar{D}_i - D^1}{\bar{D}_i - \underline{D}_i} \ln \left(\frac{\bar{D}_i - \underline{D}_i}{\bar{D}_i - D^1} \right), & \text{Case} = (3, 3, 3, 3). \end{cases}
\end{aligned} \tag{23}$$

Next, we derive the conditional density function for v_i^j when $k^j = 2$. With observations at multiple levels, the range of x and y is in general restricted to $[\underline{D}_x, \bar{D}_x)$ and $(\underline{D}_y, \bar{D}_y]$, where $\underline{D}_i \leq \underline{D}_x \leq \bar{D}_x \leq \underline{D}_y \leq \bar{D}_y \leq \bar{D}_i$. Given v_i^j , the possible range of x is further restricted to $[D_l(v_i^j), D_h(v_i^j))$, where:

$$D_l(v_i^j) = \max \left\{ \underline{D}_x, D^j - \frac{200 - v_i^j}{v_i^j - \underline{v}_i} (\bar{D}_y - D^j) \right\}, \tag{24}$$

$$D_h(v_i^j) = \min \left\{ \bar{D}_x, D^j - \frac{200 - v_i^j}{v_i^j - \underline{v}_i} (\underline{D}_y - D^j) \right\}. \tag{25}$$

Using equation (11) and considering narrower integration ranges, the conditional density

function for v_i^j is computed as follows:

$$\begin{aligned}\varphi\left(v_i^j \mid \mathbf{Case}\right) &= \int_{D_l(v_i^j)}^{D_h(v_i^j)} \frac{(200 - \underline{v}_i)(D^j - x)}{(\overline{D}_y - \underline{D}_y)(200 - v_i^j)^2} \left(\frac{1}{\overline{D}_x - \underline{D}_x}\right) dx \\ &= \frac{200 - \underline{v}_i}{2(\overline{D}_x - \underline{D}_x)(\overline{D}_y - \underline{D}_y)(200 - v_i^j)^2} \left[\left\{ D^j - D_l(v_i^j) \right\}^2 - \left\{ D^j - D_h(v_i^j) \right\}^2 \right].\end{aligned}\quad (26)$$

When Case 2 is observed at multiple contamination levels, we use the conditional density for v_i^j at the highest D^j to compute the corresponding likelihood function. In the estimation procedure, we thus use the following logarithmic likelihood function for $\mathbf{v}_i = (v_i^1, v_i^2, v_i^3, v_i^4)$:

$$\ln L(\mathbf{v}_i \mid \Theta, D^1, D^2, D^3, D^4) = \begin{cases} \ln \Pr(\mathbf{Case}), & \text{if } k^j \neq 2 \text{ for } j = 1, 2, 3, 4 \\ \ln \Pr(\mathbf{Case}) + \ln \varphi(v_i^{j^*} \mid \mathbf{Case}), & \text{otherwise,} \end{cases} \quad (27)$$

where

$$j^* = \max \left\{ j \mid \underline{v}_i < v_i^j < 200 \right\}. \quad (28)$$

3.3 On measurement errors

In applying our statistical model with idiosyncratic shocks to the survey data for an estimation purpose, we may face a serious measurement error problem. We have so far assumed that when Case 2 is observed, the actual valuation by consumer i (v_i) is identical to the true valuation (v_i^*). As discussed above, however, with two or more observations included in Case 2, the range of v_i^* is restricted further from either the above or the below. In addition, the range of v_i^* is bounded from the below by the presence of a threshold (\underline{v}_i). Consequently, the actual valuation v_i may be outside the theoretically consistent range of the true valuation v_i^* .

The first type of measurement errors: To deal with these issues, we introduce measurement errors in two ways; one is rather crude, and the other is relatively sophisticated. Both types of measurement errors are applied to a case where the discounted valuation at the highest contamination level is adopted. In this case, as mentioned before, the range of v_i^* is bounded from the above because the upper bound of x is determined jointly by \overline{D} and the lowest contamination level among those included in Case 2, and it is bounded from the below due to the presence of a threshold \underline{v}_i (≥ 0).

For the first type of measurement errors, it is assumed that not only \overline{D} , but also \underline{v}_i is exogenously given; that is, \underline{v}_i is set at \underline{v} for all consumers. We then treat the observed valuation as the true valuation when v_i is between the upper limit of v_i^* and its lower limit. However, if v_i is greater than the upper limit of v_i^* , then v_i is reset at $\max(v_i^*)$, and if v_i is smaller than the lower limit of v_i^* , then v_i is reset at \underline{v} . It is further assumed that the overvaluation ($v_i > \max(v_i^*)$) takes place with probability $\overline{\pi}$, and that the undervaluation ($v_i < \underline{v}$) occurs with probability $\underline{\pi}$. Consequently, v_i is observed without any measurement error with probability $1 - \overline{\pi} - \underline{\pi}$. The above way to treat measurement errors is *ad hoc*, but operational in that the magnitude of errors is independent of the true valuation v_i^* .

The second type of measurement errors: As the second method, we specify a simple density function for measurement errors ($g_1(v_i | v_i^*)$) by two linear functions.

$$g_1(v_i | v_i^*) = \begin{cases} \frac{200-v_i^*}{100v_i^{*2}} v_i, & \text{if } v_i \leq v_i^*, \\ \frac{v_i^*}{100(200-v_i^*)^2} (200 - v_i), & \text{otherwise.} \end{cases} \quad (29)$$

By construction, $\int_0^{200} g_1(v | v_i^*) dv = 1$ and $\int_0^{200} [v g_1(v | v_i^*)] dv = v_i^*$ hold. Hence, the above formulation of measurement errors does not yield any systematic bias. See Figure 7-1 for a shape of the above density function.

An alternative, and even simpler density function for measurement errors ($g_2(v_i | v_i^*)$) is formulated by two uniform distributions.

$$g_2(v_i | v_i^*) = \begin{cases} \frac{200-v_i^*}{100v_i^*}, & \text{if } v_i \leq v_i^*, \\ \frac{v_i^*}{100(200-v_i^*)}, & \text{otherwise.} \end{cases} \quad (30)$$

By construction, $\int_0^{200} g_2(v | v_i^*) dv = 1$ and $\int_0^{200} [v g_2(v | v_i^*)] dv = v_i^*$ hold again. Hence, the above formulation of measurement errors does not yield any systematic bias either. See Figure 7-2 for a shape of the above density function.

Given the above type of measurement errors, the logarithmic likelihood is defined as follows:

$$\ln \Pr(\mathbf{Case}) + \ln \int_{\underline{v}_i}^{\max v_i^*} \left[\varphi(v | \mathbf{Case}) g_k(v_i^{j*} | v) \right] dv, \quad (31)$$

where k is 1 or 2. It is possible to compute analytically the integral in equation (31) in both cases ($k = 1$ and 2).

4 Questionnaire survey results

4.1 The way in which an internet-based questionnaire survey was conducted

To investigate the consumers' response to radiation-contaminated milk, we charged the Survey Research Center (hereafter, SRC), a Tokyo-based private research institute, to conduct an internet-based questionnaire survey in the second half of August, 2011. The SRC had a large-scale panel of those who were currently living in the Tokyo metropolitan area, and provided us with the sample consisting of 760 male and 760 female respondents for each age group of twenties, thirties, forties, fifties, and sixty or older. Thus, the total sample size amounts to 7,600.

As mentioned in the introduction, following the safety measure recommended by the ICRP, the Japanese government set the upper limit of cesium contained in milk at 200 Bq/kg. Given this safety standard, the annual radiation exposure through drinking contaminated milk every day amounts to at most 5 millisievert per year, and a life-time probability of the incidence of cancer increases by only 0.025%.

After providing a brief description about the official safety standard of radiation contamination, we asked each respondent which kind of preference he/she revealed in response to one liter pack of milk which was supposed to be contaminated at the level of 10 Bq/kg, 50 Bq/kg, 100 Bq/kg, or 200 Bq/kg, when he/she was assumed to purchase such slightly radiation-contaminated milk for his/her own drinking purpose. Each respondent chose either to purchase it at a normal price (assumed to be 200 yen), to discount it below 200 yen, or to refuse to purchase it at any positive price.² A respondent who chose to discount it was further asked to write down a discount price up to one digit between 0 yen and 200 yen; for example, a quoted discount price may be 121 yen or 98 yen.

Besides preferences for radiation-contaminated milk, we inquired about some of respondents' characteristics. With respect to annual income classes, 726 respondents (9.6% of the entire sample) belonged to (i) less than two million yen, 2,685 (35.3%) to (ii) between two and five million yen, 3,042 (40.0%) to (iii) between five and ten million yen, and 1,147 (15.1%) to (iv) ten million yen or more.

²A respondent who lived with children was given a set of the same questions in a case where he/she purchased radiation-contaminated milk for his/her children. However, the corresponding responses are not used in this study.

In terms of household structure, 4,700 respondents out of 7,600 (61.8%) had a spouse. 4,571 respondents (60.1%) did not live with any children, while 1,508 respondents (19.8%) lived with one child, 1,231 (16.2%) with two children, 246 (3.2%) with three children, and 44 (0.6%) with four or more children. The age of the youngest child was between zero and two years old for 506 respondents (16.7%), between three and five for 289 (9.5%), between six and ten for 368 (12.1%), between eleven and fifteen for 409 (13.5%), between sixteen and twenty for 454 (15.0%), and twenty or older for 1,003 (33.1%).

About a preference for luxury items, 1,546 respondent (20.3%) smoked regularly, while 1,871 (24.6%) drank frequently. 363 respondents (4.8%) purchased organic vegetables regularly, 3,631 (47.8%) sometimes, and 3,606 (47.4%) never. In terms of other health-related issues, 3,335 respondents (43.9%) participated in cancer insurance, and 4,071 (53.6%) had a checkup at least once a year.

As a somewhat delicate question, we asked each respondent about the possibility that he/she would suffer from fatal cancer in the course of lifetime. 634 respondents (8.3%) thought that they were unlikely to suffer from fatal cancer. On the other hand, 1,392 respondents (18.3%) considered the probability to be below the national average (around thirty percent per life-time), 2,798 (36.8%) approximately equal to it, and 1,235 (16.3%) above it. 1,514 respondents (19.9%) answered that they could not judge about the probability of cancer incidence, while 27 (0.4%) did not answer at all.

As to a preference for normal milk, which may have a substantial impact on the valuation of radiation-contaminated milk, 2,594 respondents (34.1%) drank milk almost every day, 3,496 (46.0%) sometimes, and 1,510 (19.9%) never.

4.2 The frequency of the three cases and the distribution of quoted discount prices

As reported in Table 1, respondents are more and more averse toward contaminated milk as the contamination level is higher. The share of Case 1 where a respondent purchases contaminated milk without any discounting decreases as the contamination level increases from 10 Bq/kg to 200 Bq/kg; it is 15.6% for 10 Bq/kg, 11.7% for 50 Bq/kg, 8.8% for 100 Bq/kg, and 5.6% for 200 Bq/kg. The proportion of Case 2 where a respondent discounts contaminated milk also decreases with the contamination level; it is 38.6% for 10 Bq/kg, 28.1% for 50 Bq/kg, 19.9% for 100 Bq/kg, and 13.2% for 200

Bq/kg. On the other hand, the share of Case 3 where a respondent never purchases contaminated milk at any positive price increases with the contamination level; it is 45.8% for 10 Bq/kg, 60.1% for 50 Bq/kg, 71.2% for 100 Bq/kg, and 81.2% for 200 Bq/kg.

We observe all possible fifteen patterns in the combination of the three cases which emerges as a contamination level increases from 10 Bq/kg to 50 Bq/kg, 100 Bq/kg, and 200 Bq/kg. Among 7,204 respondents whose valuation of contaminated milk is not increasing in contamination levels, 382 (5.3%) evaluate contaminated milk at 200 yen for the four levels (**Case** = (1, 1, 1, 1)), while 3,353 (46.5%) find zero valuation for all levels (**Case** = (3, 3, 3, 3)).

Out of 7,204 respondents, 449 (6.2%) skip Case 2 as a contamination level increases, or belong to **Case** = (1, 1, 1, 3), (1, 1, 3, 3), or (1, 3, 3, 3), while 1,185 (16.4%) include Case 2 only once, or belong to **Case** = (1, 1, 1, 2), (1, 1, 2, 3), (1, 2, 3, 3), or (2, 3, 3, 3). On the other hand, 1,142 (15.9%) individuals include Case 2 two or three times, or belong to **Case** = (1, 1, 2, 2), (1, 2, 2, 2), (1, 2, 2, 3), (2, 2, 2, 3), or (2, 2, 3, 3). 693 respondents (9.6%) quote discount prices for the four levels (**Case** = (2, 2, 2, 2)).

As mentioned above, those who were interested in purchasing contaminated milk at discount prices were asked to write down a discount price up to one digit between zero yen and 200 yen. As shown in Table 2, the average quoted price decreases with the contamination level; it is 134.9 yen for 10 Bq/kg, 130.8 yen for 50 Bq/kg, 125.4 yen for 100 Bq/kg, and 119.9 for 200 Bq/kg.

As shown in Figure 8-1, a respondent tended to quote a discount price at 10-yen intervals for a higher range, and at 50-yen intervals for a lower range. Accordingly, the median of quoted prices is a round number; it is 150 yen for 10 Bq/kg, 150 yen for 50 Bq/kg, 140 yen for 100 Bq/kg, and 120 yen for 200 Bq/kg.

Figure 8-2 depicts the histogram of the quoted discount prices at 50-yen intervals. As demonstrated by this figure, the overall frequency reduces, and the mode shift downward as the contamination level increases.

4.3 Determinants of the respondents' original perception of their own cancer risks

In our questionnaire survey, each respondent was inquired about the risk perception of cancer incidence. Here, we construct a dummy variable which takes one for those

who considered their own cancer risks to be lower than the national average (about thirty percent per life-time), and otherwise zero. Then, using this dummy variable as a dependent variable, we conduct the logit estimation. The summary statistics of explanatory variables are documented in Table 3, while the estimation result is reported in Table 4.

According to Table 4, the tendency for respondents to consider cancer risks to be rather low is noticeable among those above the age of sixty, non-smokers, those with a habit of eating organic vegetables and having a regular checkup, and non-holders of cancer insurance. If older respondents might have thought that they had survived cancer risks, the above estimation result may be subject to a sample selection bias. In the next section, we use as an explanatory variable the predicted cancer risk perception which is based on the logit estimation. The average of the predicted value is 26.8%.

5 Estimation results

5.1 A preliminary examination of the distribution of quoted discount prices in Case 2

Before conducting estimation procedures, we examine with extreme care how quoted discount prices are distributed in Case 2. First of all, we drop the observations in which the valuation of radiation-contaminated milk increases with the contamination levels. Consequently, the sample size reduces from 7,600 to 7,204.

As discussed before, when the discounted valuation at the highest level is adopted among multiple observations included in Case 2, the range of the true valuation (v_i^*) is restricted from the above, depending on the value of \bar{D} . In the presence of a threshold (\underline{v}_i), its range is further bounded from both the below and the above.

Let us first examine the case where a threshold is absent ($\underline{v}_i = 0$), and \bar{D} is set at 500 Bq/kg.³ In **Case** = $(k^1, k^2, k^3, k^4) = (1, 1, 2, 2)$ (**Pattern 4**), $(1, 2, 2, 2)$ (**Pattern 7**), $(1, 2, 2, 3)$ (**Pattern 8**), $(2, 2, 2, 2)$ (**Pattern 11**), $(2, 2, 2, 3)$ (**Pattern 12**), and $(2, 2, 3, 3)$ (**Pattern 13**), among not a few respondents, the reported valuation v_i is beyond the theoretically consistent upper limit of v_i^* . More precisely, 924 out of 1,835 respondents included in the above six patterns violates the theoretical upper limit of v_i^* . That is, the number of the observations with violation is 20 out of 45 in Pattern 4, 13 out of 32

³As of November, 2011, there had been cases where the contamination level was reported to outside the established standard (200 Bq/kg), but the reported level had never exceeded 500 Bq/kg.

in Pattern 7, 15 out of 44 in Pattern 8, 317 out of 693 in Pattern 11, 238 out of 457 in Pattern 12, and 321 out of 564 in Pattern 13.

In the presence of a threshold ($\underline{v}_i > 0$), two additional effects are generated. First, the valuation of a discount price is bounded not only from the above, but also from the below at \underline{v}_i in the above patterns. In addition to the six patterns, the lower bound arises in the following four patterns: **Case** = $(k^1, k^2, k^3, k^4) = (1, 1, 1, 2)$ (**Pattern 2**), $(1, 1, 2, 3)$ (**Pattern 5**), $(1, 2, 3, 3)$ (**Pattern 9**), and $(2, 3, 3, 3)$ (**Pattern 14**). Obviously, the number of the observations which violate the lower bound of v_i^* increases with \underline{v}_i .

Second, the theoretical upper bound of v_i^* is relaxed due to a larger threshold \underline{v}_i . Accordingly, the number of the observations which violate the upper bound of v_i^* decreases with \underline{v}_i .

To see a change in the number of the observations with violation by an increase in a threshold, we set \overline{D} at 500, and raise \underline{v} as a common value for a threshold from zero to 190 at 10-yen intervals. The number of the observations which violate the lower bound increases from zero ($\underline{v} = 0$) to 3,015 out of 3,020 ($\underline{v} = 190$). On the other hand, the number of the observations which violate the upper bound decreases from 924 out of 1,835 ($\underline{v} = 0$) to 3 ($\underline{v} = 190$). Consequently, the total number of the observations with violation is smallest at $\underline{v} = 90$.

We can observe more details about the above phenomena by Figures 9-1 and 9-2. The six histograms in Figure 9-1 depict the distribution of quoted discount prices for the patterns in which two or more observations are included in Case 2 (Patterns 4, 7, 8, 11, 12, and 13). In each histogram, two black (yellow or red) vertical lines represent the theoretical range of v_i given $\underline{v} = 0$ (50 or 100). The four histograms in Figure 9-2, on the other hand, depict the distribution of quoted prices for the patterns in which only one observation is included in Case 2 (Pattern 2, 5, 9, and 14).

Given a large number of the observations with violation, the treatment of measurement errors is quite important in estimation procedures.

5.2 Estimation results under the first type of measurement errors

Under the first type of measurement errors, once the observed valuation violates the theoretical range of the true valuation, it is replaced by the theoretical upper (lower) limit. A major drawback of this adjustment method is that neither \overline{D} nor \underline{v}_i can be estimated, and both need to be predetermined. Given such a restrictive nature, estimation results

under the first type of measurement errors have to be treated as tentative ones.

Table 5 reports the estimation results for \underline{D}_i in the cases with and without a threshold (\underline{v}_i).⁴ In the absence of a threshold, it is assumed that $\overline{D} = 500$ and $\underline{v}_i = 0$ for all consumers. As reported in the first panel of Table 5, most individual characteristics have significant impacts on the determinants of \underline{D}_i in the case without any threshold. Recall that lower \underline{D}_i implies stronger preferences for zero radiation risks.

A preference for zero radiation risks is strong among younger females with infants, while it is weak among older males without any child. An interesting observation is that a preference for zero risks is strong among high income individuals. Probably due to more restrictive budget constraints, individuals with more children tend to have a weaker preference for zero risks.

As to cancer-risk-related variables, a preference for zero risks is weaker among regular smokers and/or drinkers, those who are not interested in eating organic vegetables or having a regular health checkup. Restating these results, a preference for zero radiation risks is weak among those who are regarded as having already carried considerable cancer risks.

When a set of the above cancer-risk-related variables are replaced by the prediction of a cancer risk perception based on the logit estimation (Table 4), we find that a preference for zero risks is strong among those who perceive their own cancer risks to be small. That is, those who originally perceive their own cancer risks to be rather low are unlikely to purchase contaminated milk at even heavily discount prices. Note that those who never drink evaluate contaminated milk substantially downward.

The second panel of Table 5 reports the estimation results for the case with a threshold ($\underline{v}_i > 0$). With $\overline{D} = 500$, we assume $\underline{v}_i = 90$ for all consumers because the number of the observations which violate the theoretical range of the true valuation is smallest at $\underline{v}_i = 90 \forall i$.

The overall estimation results do not differ substantially between the cases with/without a threshold. But, the significance level of estimated coefficients is lower in the case with a threshold.

⁴It is assumed that the overvaluation, exact valuation, and undervaluation take place with equal probability.

5.3 Estimation results under the second type of measurement errors

Under the second type of measurement errors, we can estimate not only a systematic part of \underline{D}_i , but also a systematic part of \underline{v}_i , and a parameter \overline{D} , which is assumed to be common among respondents. Accordingly, not only the degree of zero risk preferences which is measured by $\kappa_i = \frac{-\underline{D}_i}{\overline{D} - \underline{D}_i}$, but also the risk-adjusted weight which is represented by $\frac{\hat{p}_i}{p_i} = \frac{200}{200 - \underline{v}_i}$ or equation (2), can be inferred from such estimation results. Note that lower \underline{D}_i implies stronger zero risk preferences, while higher \underline{v}_i (a threshold) indicates larger risk-adjusted weights.

Table 6 reports estimation results in a case where a combination of two linear functions is adopted as a density function of measurement errors. As shown in the estimation about \underline{D}_i , the estimated effects of individual characteristics on zero risk preferences are similar to those of Table 5. A preference for zero radiation risks is strong among younger females with infants, while it is weak among older males without any child. However, neither income class nor the number of children has any significant effect on a preference for zero risks. As to cancer-risk-related variables, a preference for zero risks is weaker among regular smokers and/or drinkers. In addition, those who never drink evaluate contaminated milk downward.

In terms of the estimation of \underline{v}_i , females, the old, the rich, and those with infants, but fewer children tend to apply larger risk-adjusted weights, thereby having higher threshold points in valuation of radiation-contaminated milk. The estimated parameter of \overline{D} , significant at 260.8, is above 210 Bq/kg of cesium which was detected on March 20th, 2011.

Table 6 reports another specification where a set of the above cancer-risk-related variables are replaced by the prediction of a cancer risk perception based on the logit estimation (Table 4).⁵ As to a systematic part of \underline{v}_i , we also drop age dummies because older respondents have both larger risk-adjusted weights and lower perception of cancer risks. We find that those who perceive their own cancer risks to be small tend to have a fairly strong preference for zero risks as well as a pretty large risk-adjusted weight. More concretely, the estimated coefficient on the logit-fitted-value is -1003.8 in \underline{D}_i and 41.0 in \underline{v}_i .

⁵Rigorously, when we include the logit-fitted-value as an explanatory variable in a nonlinear system in order to treat endogeneity, its coefficient may not be consistent. Here, we consider an endogeneity problem in a somewhat *ad hoc* way at the expense of improper treatment of nonlinearity.

5.4 On a possibility of secondary markets

As discussed in Section 2, the degree of zero risk preferences κ_i , defined as $\frac{-D_i}{D-\underline{D}_i}$, serves as a key parameter in determining whether secondary markets are robust with respect to radiation contamination. That is, if $\kappa_i < 0.632$, then a secondary market substitutes to some extent for a primary market among those whose characteristics are similar to that of consumer i . Conversely, if $\kappa_i > 0.632$, then both primary and secondary markets shrink simultaneously among those resemble to consumer i in terms of individual characteristics.

In addition, we can infer from estimated \underline{v}_i , the risk-adjusted weight which is represented by $\frac{\hat{p}_i}{\bar{p}_i} = \frac{200}{200-\underline{v}_i}$. This risk-adjusted weight implies the extent that a subjective probability of cancer occurrence is augmented by extreme aversion to radiation risks. Obviously, the higher \underline{v}_i is, the larger the risk-adjusted weight is.

Table 7 reports the value of κ_i is computed together with a 95% confidence interval based on the estimation results reported by Table 5. Given that \underline{v}_i cannot be estimated in this case, we do not have any inference about the risk-adjusted weight. According to the first panel of Table 7, the computed value of κ_i for the case without any threshold is on either side of 0.632, depending on individual characteristics. For example, a point estimate of κ_i is 0.686 with a 95% confidence interval between 0.653 and 0.718 for a female regular drinker of milk, of the age of twenties, with one infant, an annual income between two and five million yen, uninterested in smoking or drinking, but interested in eating organic vegetables and having a regular health checkup.

On the other hand, a point estimate of κ_i is 0.288 with a 95% confidence interval between 0.202 and 0.374 for a male regular drinker of milk, sixty years old or older, not living with any child, an annual income between two and five million yen, interested in smoking and drinking, but uninterested in eating organic vegetables or having a regular health checkup. As shown in the second panel of Table 7, the pattern observed in the cases with thresholds is similar to that of those without any threshold, but the overall valuation of κ_i increases in any case.

Table 8-1 reports the computed values of both κ_i and $\frac{\hat{p}_i}{\bar{p}_i}$ for the case where cancer-risk-related variables are used as explanatory variables, while Table 8-2 briefs those values for the case where they are replaced by the logit-fitted-value. According to the first panel of Table 8-1, most point estimates of κ_i are above 0.632. The computed value of κ_i is barely below 0.632 for a male regular drinker of milk, sixty years old or older, not living with any child, and interested in smoking and drinking. As shown in the

second panel of Table 8-1, the computed value of the risk-adjusted weight does not differ substantially among respondents. For example, it is around two for young males and about three for old females.

As reported in Table 8-2, on the other hand, the degree of zero risk preferences as well as the risk-adjusted weight differ substantially among respondents, depending on whether he/she perceives his/her own cancer risk to be rather low. For example, an old male who perceives his cancer risk to be high carries $\kappa_i = 0.466$ much lower than 0.632, and applies risk-adjusted weights around two times as large as his subjective probability. On the other hand, a young female with an infant who perceives her cancer risk to be low has $\kappa_i = 0.895$ much higher than 0.632, and applies risk-adjusted weights more than five times as large as her subjective probability.

The overall results suggest that if the individual characteristics are conditioned by respondents' perception about cancer risks, then how a preference for zero risks is strong, and how large the risk-adjusted weight is depend critically on whether a respondent perceives his/her cancer risk to be low. Concretely, those who perceive their own cancer risk to be rather low reveal strong preferences for zero risks in deciding whether they purchase radiation-contaminated milk, and demonstrate extreme aversion toward radiation risks in determining how much contaminated milk is discounted.

6 Conclusion

This paper presents a simple theoretical model to explain consistently heterogeneous patterns in consumers' valuation on radiation-contaminated milk by explicitly incorporating a strong preference for zero radiation risks. In particular, it establishes a rigorous condition under which contaminated milk is still traded at discount prices even when contamination levels are relatively high. Using an internet-based questionnaire survey consisting of 7,600 respondents, we empirically explore whether the above condition holds. According to estimation results, as milk contains more radiation, a contaminated milk market disappears quickly among those who originally perceive their own cancer risks to be rather low. Conversely, contaminated milk is still traded at discount prices among those who are regarded as having already carried considerable cancer risks.

(to be completed)

Appendix 1: Conditional distribution for v in Case 2

In this appendix, we prove two propositions about the conditional distribution for v in Case 2.

Proposition 1 \hat{v} in equation (13) is the median of the conditional distribution for v given $\underline{v}_i \leq v < 200$.

Proof. From equation (12), the conditional density function $\varphi(v(y)|x < D < y)$ is continuous for $v \in [\underline{v}_i, 200)$. And, the conditional probability of the event ' $\underline{v}_i \leq v < \hat{v}$ ' given $\underline{v}_i \leq v < 200$ is calculated as follows:

$$\begin{aligned} \Pr(\underline{v}_i \leq v < \hat{v} | \underline{v}_i \leq v < 200) &= \int_{\underline{v}_i}^{\hat{v}} \frac{(200 - \underline{v}_i)(D - \underline{D}_i)}{2(\overline{D} - D)(200 - v)^2} dv \\ &= \frac{(200 - \underline{v}_i)(D - \underline{D}_i)}{2(\overline{D} - D)} \left[\frac{1}{200 - v} \right]_{\underline{v}_i}^{\hat{v}} \\ &= \frac{1}{2}. \end{aligned} \tag{32}$$

Because $\varphi(v(y)|x < D < y)$ is continuous for $v \in [\underline{v}_i, 200)$, equation (32) means that $\Pr(\hat{v} \leq v < 200 | \underline{v}_i \leq v < 200) = 1 - \Pr(\underline{v}_i \leq v < \hat{v} | \underline{v}_i \leq v < 200) = \frac{1}{2}$. Therefore, \hat{v} is the median of the conditional distribution for v given $\underline{v}_i \leq v < 200$. ■

Proposition 2 \hat{v} in equation (13) is the mode of the conditional distribution for v given $\underline{v}_i \leq v < 200$.

Proof. From equation (12), the derivative of $\varphi(v(y)|x < D < y)$ with respect to v is calculated as follows:

$$\frac{\partial \varphi(v(y)|x < D < y)}{\partial v} = \begin{cases} \frac{(200 - \underline{v}_i)(D - \underline{D}_i)}{2(\overline{D} - D)(200 - v)^3} \geq 0, & \underline{v}_i \leq v < \hat{v} \\ -\frac{(200 - \underline{v}_i)(\overline{D} - D)}{2(D - \underline{D}_i)(v - \underline{v}_i)^3} \leq 0, & \hat{v} \leq v < 200. \end{cases} \tag{33}$$

Further, $\varphi(v(y)|x < D < y)$ is continuous at $v = \hat{v}$. Therefore, $\varphi(v(y)|x < D < y)$ takes the largest value at $v = \hat{v}$, and \hat{v} is the mode of the conditional distribution. ■

References

- [1] Kahneman, Daniel, and Amos Tversky, 1979, “Prospect theory: An analysis of decision under uncertainty,” *Econometrica* 47:2, 263–291.

(to be completed)

Table 1: The share of the respondents classified according to the three cases

	Case 1: a purchase without any discounting	Case 2: a purchase with discounting	Case 3: no purchase at any price	total
10 Bq	1,189	2,934	3,477	7,600
	(15.6%)	(38.6%)	(45.8%)	
50 Bq	892	2,137	4,571	7,600
	(11.7%)	(28.1%)	(60.1%)	
100 Bq	670	1,516	5,414	7,600
	(8.8%)	(19.9%)	(71.2%)	
200 Bq	428	1,000	6,172	7,600
	(5.6%)	(13.2%)	(81.2%)	

Table 2: Distribution and statistics of discount prices quoted in Case 2

[illegible]

Table 3: Descriptive statistics of explanatory variables

	Mean	Standard Deviation
male dummy	0.5	
age dummy		
(twenties)	0.2	
(thirties)	0.2	
(forties)	0.2	
(fifties)	0.2	
income class	2.607	0.855
spouse dummy	0.618	
the number of children	1.643	0.904
the age of the youngest child		
without any child	0.601	
younger than 3 years old	0.067	
between 3 and 10	0.086	
between 11 and 15	0.054	
between 16 and 20	0.060	
over 20	0.132	
smoker dummy	0.203	
drinker dummy	0.246	
no habit of eating organic vegetables	0.474	
participation in cancer insurance	0.439	
regular health checkup	0.536	
no habit of drinking milk	0.199	
the predicted cancer risks based on the logit estimation	0.268	

Table 4: Estimation result of the logit model for respondents' perception of cancer risks

explanatory variables	A dummy variable of those who perceive cancer risks to be lower than the national average			
	Coefficient		Marginal effect	
male dummy	0.135 (0.055)	**	0.026 (0.011)	**
age dummy (twenties)	-0.467 (0.086)	***	-0.085 (0.014)	***
(thirties)	-0.481 (0.084)	***	-0.087 (0.014)	***
(forties)	-0.364 (0.082)	***	-0.067 (0.014)	***
(fifties)	-0.068 (0.079)		-0.013 (0.015)	
smoker dummy	-0.314 (0.071)	***	-0.058 (0.012)	***
drinker dummy	-0.039 (0.064)		-0.008 (0.012)	
no habit of eating organic vegetables	-0.137 (0.054)	**	-0.026 (0.011)	**
participation in cancer insurance	-0.365 (0.056)	***	-0.070 (0.011)	***
regular health checkup	0.046 (0.055)		0.009 (0.011)	
constant	-0.545 (0.075)	***		
Number of observations	7573			
Wald chi-squared	125.5			
P-value of chi-square test	0.0000			
Pseudo R squared	0.0143			
Log likelihood	-4335.5			

Note 1: A dependent dummy variable takes one for a respondent who perceive life-time cancer risk to be lower than the national average.

Note 2: *, **, and *** implies the significance level at 10%, 5% and 1% respectively.

Note 3: Among 7600 respondents, 27 did not answer the question concerning the perception of cancer risks.

Table 5: Maximum likelihood estimation results for \underline{D} with $\bar{D} = 500$
under the first type of measurement errors

	$\underline{v} = 0$				$\underline{v} = 90$			
	Specification 1		Specification 2		Specification 1		Specification 2	
male dummy	268.55 (29.39)	***	309.87 (27.34)	***	202.67 (39.30)	***	248.14 (37.89)	***
age dummy (twenties)	-160.32 (43.45)	***	-180.64 (47.78)	***	-272.36 (65.90)	***	-305.29 (75.01)	***
(thirties)	-171.86 (44.90)	***	-203.62 (51.60)	***	-321.45 (52.35)	***	-368.66 (67.71)	***
(forties)	-160.48 (45.22)	***	-189.02 (50.30)	***	-283.18 (66.39)	***	-318.76 (76.43)	***
(fifties)	-105.09 (39.68)	***	-96.12 (39.89)	**	-202.08 (49.12)	***	-198.49 (57.07)	***
income class	-71.73 (15.67)	***	-79.02 (15.07)	***	-28.14 (23.83)		-37.66 (23.14)	
spouse dummy	-28.36 (32.82)		-41.15 (32.98)		-22.21 (44.68)		-21.62 (46.63)	
the number of children	68.69 (33.78)	**	74.24 (28.55)	***	38.69 (43.57)		46.91 (44.60)	
youngest child age dummy (between 0 and 2)	-321.21 (97.81)	***	-327.43 (90.66)	***	-238.61 (121.95)	*	-262.45 (124.01)	**
(between 3 and 10)	-238.56 (87.57)	***	-249.19 (81.59)	***	-116.61 (114.27)		-130.20 (114.34)	
(between 11 and 15)	-194.12 (93.95)	**	-205.49 (88.61)	**	-159.67 (128.95)		-173.90 (82.11)	**
(between 16 and 20)	-159.58 (83.90)	*	-164.73 (78.99)	**	-87.62 (114.95)		-99.96 (115.19)	
(over 20)	-153.34 (66.41)	**	-179.61 (60.52)	***	-97.48 (73.18)		-135.56 (89.32)	
smoker dummy	54.03 (29.40)	*			71.41 (44.65)			
drinker dummy	68.44 (28.10)	**			102.95 (42.43)	**		
no habit of eating organic vegetables	70.77 (25.94)	***			45.34 (37.82)			
participation in cancer insurance	-17.82 (26.37)				-22.88 (37.66)			
regular health checkup	-13.73 (25.99)				-9.36 (38.35)			
no habit of drinking milk	-635.01 (55.98)	***	-626.43 (56.00)	***	-791.24 (81.05)	***	-776.34 (81.16)	***
The predicted cancer risks based on the logit estimation			-496.89 (272.76)	*			-534.53 (425.57)	
constant	-492.52 (51.10)	***	-292.00 (102.23)	***	-748.26 (72.37)	***	-538.97 (159.30)	***
Number of observations	7204		7204		7204		7204	
Wald chi-squared	420.1		441.6		232.0		210.7	
P-value of chi-square test	0.0000		0.0000		0.0000		0.0000	
Log likelihood	-41720.4		-41728.5		-33711.5		-33717.4	

Note 1: *, **, and *** implies the significance level at 10%, 5% and 1% respectively.

Note 2: The observations in which respondents who raise v_i as the contamination level increases are dropped. Consequently, the number of observations reduces to 7204.

**Table 6: Maximum likelihood estimation results for \underline{D} , \underline{v} and \bar{D}
under the second type of measurement errors (linear density functions)**

	Specification 1						Specification 2					
	lower D		lower v		upper D		lower D		lower v		upper D	
male dummy	361.24 (47.08)	***	-10.11 (1.28)	***			412.81 (45.26)	***	-14.01 (1.09)	***		
age dummy (twenties)	-124.55 (69.68)	*	-28.89 (2.19)	***			-249.92 (75.33)	***				
(thirties)	-207.50 (72.99)	***	-30.69 (2.07)	***			-341.00 (83.29)	***				
(forties)	-171.42 (72.12)	**	-25.91 (2.36)	***			-285.03 (78.72)	***				
(fifties)	-135.68 (64.22)	**	-17.11 (1.44)	***			-171.09 (64.15)	***				
income class	-24.76 (25.46)		1.79 (0.72)	**			-23.29 (24.50)		0.67 (0.65)			
spouse dummy	-55.06 (54.03)		-1.69 (1.60)				-80.77 (53.48)		11.38 (1.38)	***		
the number of children	52.03 (55.33)		-4.24 (1.21)	***			53.40 (55.43)		-3.06 (1.21)	**		
youngest child age dummy (between 0 and 2)	-392.62 (155.25)	**	22.98 (2.24)	***			-394.43 (157.40)	**	8.84 (2.18)	***		
(between 3 and 10)	-207.55 (138.22)		16.48 (4.02)	***			-189.61 (138.85)		0.70 (3.35)			
(between 11 and 15)	-192.77 (150.21)		21.81 (4.02)	***			-176.25 (149.15)		12.41 (4.21)	***		
(between 16 and 20)	-237.26 (141.89)	*	15.31 (3.09)	***			-232.93 (141.36)	*	9.17 (2.94)	***		
(over 20)	-192.70 (109.01)	*	10.18 (2.15)	***			-225.10 (108.71)	**	19.75 (2.03)	***		
smoker dummy	81.59 (46.56)	*	-0.48 (1.43)									
drinker dummy	90.36 (44.16)	**	1.39 (1.34)									
no habit of eating organic vegetables	48.76 (41.18)		-1.29 (1.17)									
participation in cancer insurance	10.58 (42.08)		1.52 (1.12)									
regular health checkup	-0.08 (42.24)		-0.13 (1.11)									
The predicted cancer risks based on the logit estimation							-1003.82 (450.00)	**	40.98 (10.09)	***		
no habit of drinking milk	-681.61 (85.76)	***	-1.26 (1.82)				-671.62 (85.49)	***	-1.90 (1.64)			
constant	-913.90 (85.87)	***	134.28 (2.31)	***	260.84 (2.02)	***	-513.25 (166.03)	***	100.98 (3.03)	***	260.95 (2.04)	***
Number of observations	7204						7204					
Wald chi-squared	215.6						218.3					
P-value of chi-square test	0.0000						0.0000					
Log Likelihood	-29465.6						-29507.9					

Note 1: *, **, and *** implies the significance level at 10%, 5% and 1% respectively.

Note 2: The observations in which respondents who raise v_i as the contamination level increases are dropped. Consequently, the number of observations reduces to 7204.

Table 7: Estimation of κ_i for a consumer with particular characteristics based on the estimation results of Table 5Panel 1: $\underline{\nu} = 0$

gender	age	income level	marriage	number of children	age of the youngest child	smoking	drinking	habit of eating organic vegetables	participation in cancer insurance	having regular health checkup	habit of drinking milk	κ_i	(95% interval)	
male	20–29	0–200	no	0	–	no	yes	no	no	no	yes	0.388	0.330	0.446
male	30–39	500–1000	yes	1	0–2	no	no	yes	yes	yes	yes	0.649	0.609	0.688
male	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	0.577	0.527	0.626
male	over 60	200–500	yes	0	–	yes	yes	no	no	no	yes	0.288	0.202	0.374
female	20–29	200–500	yes	1	0–2	no	no	yes	no	yes	yes	0.686	0.653	0.718
female	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	0.655	0.623	0.687
female	over 60	200–500	yes	3	over 20	no	no	no	no	yes	yes	0.526	0.464	0.588

Panel 2: $\underline{\nu} = 90$

gender	age	income level	marriage	number of children	age of the youngest child	smoking	drinking	habit of eating organic vegetables	participation in cancer insurance	having regular health checkup	habit of drinking milk	κ_i	(95% interval)	
male	20–29	0–200	no	0	–	no	yes	no	no	no	yes	0.583	0.538	0.627
male	30–39	500–1000	yes	1	0–2	no	no	yes	yes	yes	yes	0.707	0.670	0.744
male	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	0.662	0.616	0.707
male	over 60	200–500	yes	0	–	yes	yes	no	no	no	yes	0.447	0.374	0.520
female	20–29	200–500	yes	1	0–2	no	no	yes	no	yes	yes	0.724	0.689	0.758
female	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	0.702	0.668	0.737
female	over 60	200–500	yes	3	over 20	no	no	no	no	yes	yes	0.607	0.546	0.668

Note 1: 95% confidence intervals for estimated κ_i are computed by the delta method.

Table 8-1: Estimation of κ_i and risk-adjusted weights for a consumer with particular characteristics based on the estimation results of Table 6Panel 1: Estimation of κ_i

gender	age	income level	marriage	number of children	age of the youngest child	smoking	drinking	habit of eating organic vegetables	participation in cancer insurance	having regular health checkup	habit of drinking milk	κ_i	(95% interval)	
male	20–29	0–200	no	0	–	no	yes	no	no	no	yes	0.683	0.635	0.732
male	30–39	500–1000	yes	1	0–2	no	no	yes	yes	yes	yes	0.824	0.793	0.855
male	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	0.789	0.750	0.828
male	over 60	200–500	yes	0	–	yes	yes	no	no	no	yes	0.626	0.553	0.699
female	20–29	200–500	yes	1	0–2	no	no	yes	no	yes	yes	0.850	0.827	0.874
female	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	0.837	0.813	0.860
female	over 60	200–500	yes	3	over 20	no	no	no	no	no	yes	0.794	0.757	0.832

Panel 2: Estimation of risk-adjusted weights

gender	age	income level	marriage	number of children	age of the youngest child	smoking	drinking	habit of eating organic vegetables	participation in cancer insurance	having regular health checkup	habit of drinking milk	risk-adjusted weight	(95% interval)	
male	20–29	0–200	no	0	–	no	yes	no	no	no	yes	1.95	1.87	2.03
male	30–39	500–1000	yes	1	0–2	no	no	yes	yes	yes	yes	2.42	2.30	2.54
male	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	2.23	2.08	2.38
male	over 60	200–500	yes	0	–	yes	yes	no	no	no	yes	2.69	2.54	2.85
female	20–29	200–500	yes	1	0–2	no	no	yes	no	yes	yes	2.70	2.53	2.88
female	40–49	500–1000	yes	2	16–20	no	no	yes	yes	yes	yes	2.51	2.32	2.70
female	over 60	200–500	yes	3	over 20	no	no	no	no	no	yes	2.96	2.74	3.18

Note 1: 95% confidence intervals are computed for estimated κ_i by the delta method, and for estimated risk-adjusted weights by one million times simulation.

Table 8-2: Estimation of κ_i and risk-adjusted weights for a consumer with particular characteristics based on the estimation results of Table 6Panel 1: Estimation of κ_i

gender	age	income level	marriage	number of children	age of the youngest child	perception of cancer risk	habit of drinking milk	κ_i	(95% interval)	
male	20-29	0-200	no	0	–	high	yes	0.589	0.429	0.749
male	30-39	500-1000	yes	1	0-2	low	yes	0.881	0.842	0.920
male	40-49	500-1000	yes	2	16-20	low	yes	0.865	0.815	0.914
male	over 60	200-500	yes	0	–	high	yes	0.466	0.145	0.787
female	20-29	200-500	yes	1	0-2	low	yes	0.895	0.865	0.925
female	40-49	500-1000	yes	2	16-20	low	yes	0.888	0.854	0.922
female	over 60	200-500	yes	3	over 20	high	yes	0.730	0.634	0.826

Panel 2: Estimation of risk-adjusted weights

gender	income level	marriage	number of children	age of the youngest child	perception of cancer risk	habit of drinking milk	risk-adjusted weight	(95% interval)	
male	0-200	no	0	–	high	yes	1.78	1.70	1.87
male	500-1000	yes	1	0-2	low	yes	3.88	2.61	5.14
male	500-1000	yes	2	16-20	low	yes	3.66	2.66	4.66
male	200-500	yes	0	–	high	yes	2.00	1.88	2.11
female	200-500	yes	1	0-2	low	yes	5.31	2.69	7.92
female	500-1000	yes	2	16-20	low	yes	4.96	3.09	6.84
female	200-500	yes	3	over 20	high	yes	2.65	2.38	2.91

Note 1: 95% confidence intervals are computed for estimated κ_i by the delta method, and for estimated risk-adjusted weights by one million times simulation.

Figure 1-1: A case without any threshold

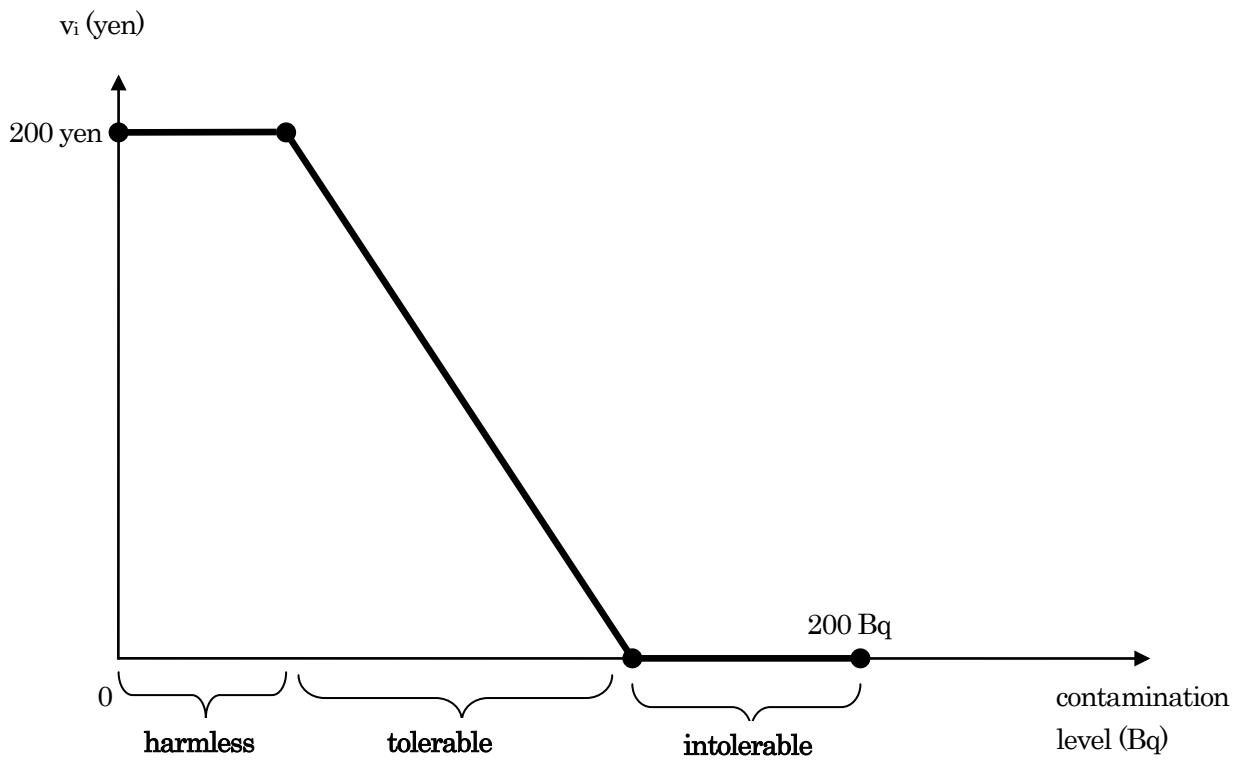


Figure 1-2: A case with a threshold

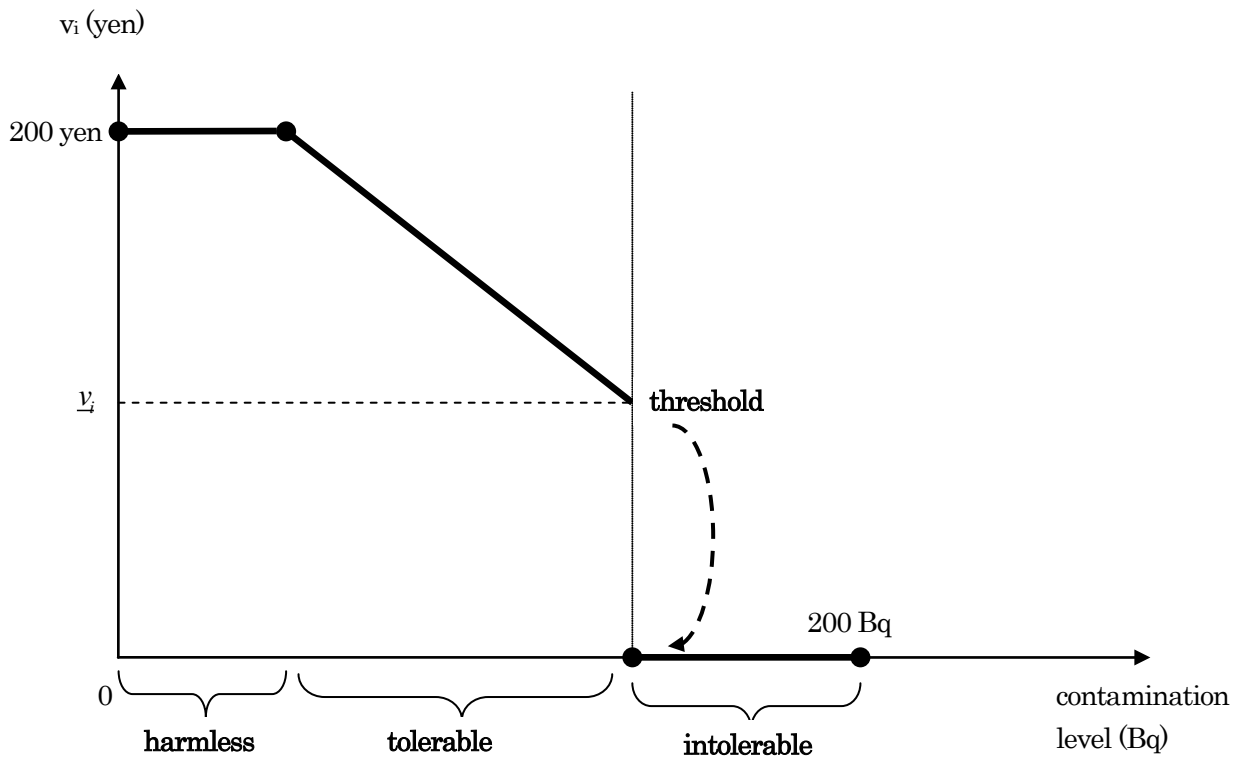


Figure 2: A pattern in a consumer's valuation of radiation-contaminated milk

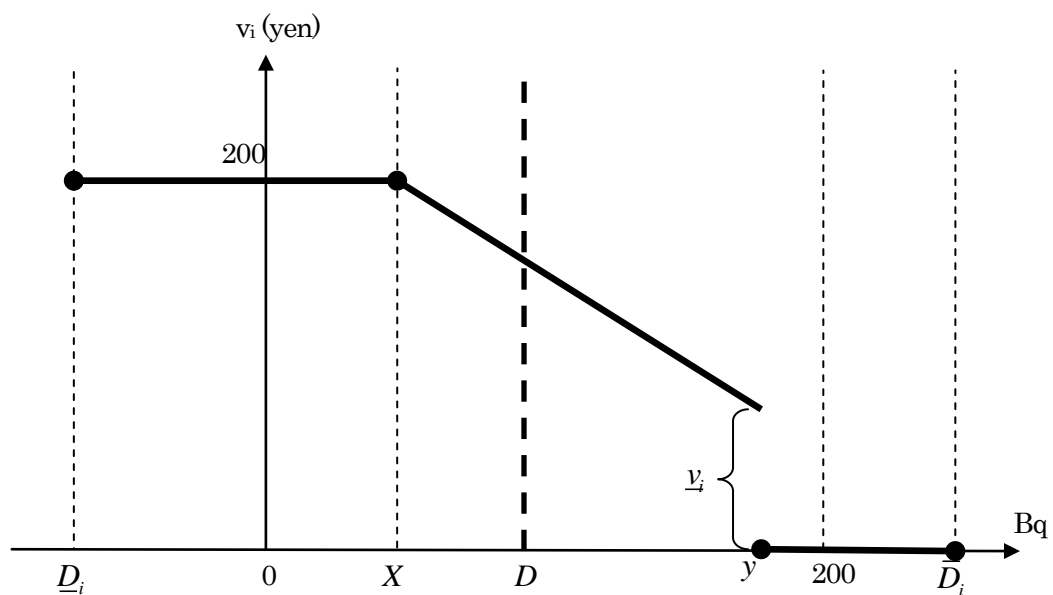


Figure 3-1: Case 1, $v_i = 200$

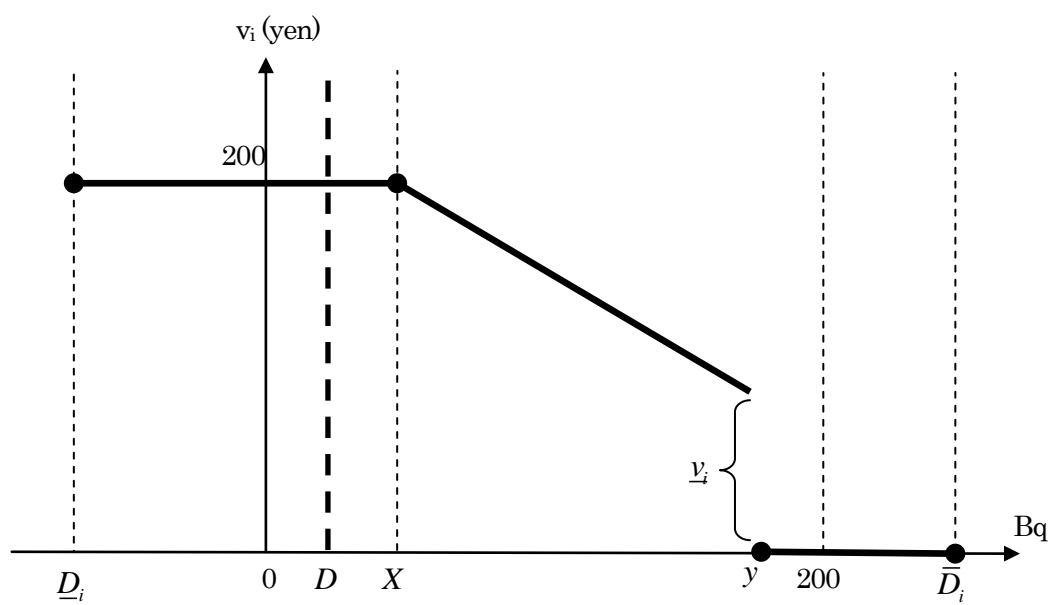


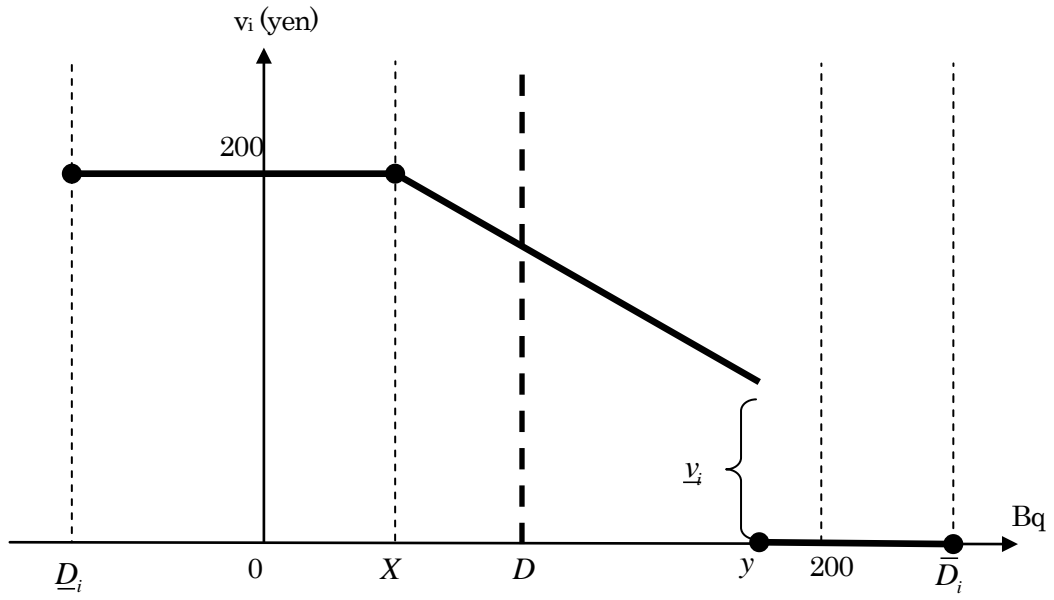
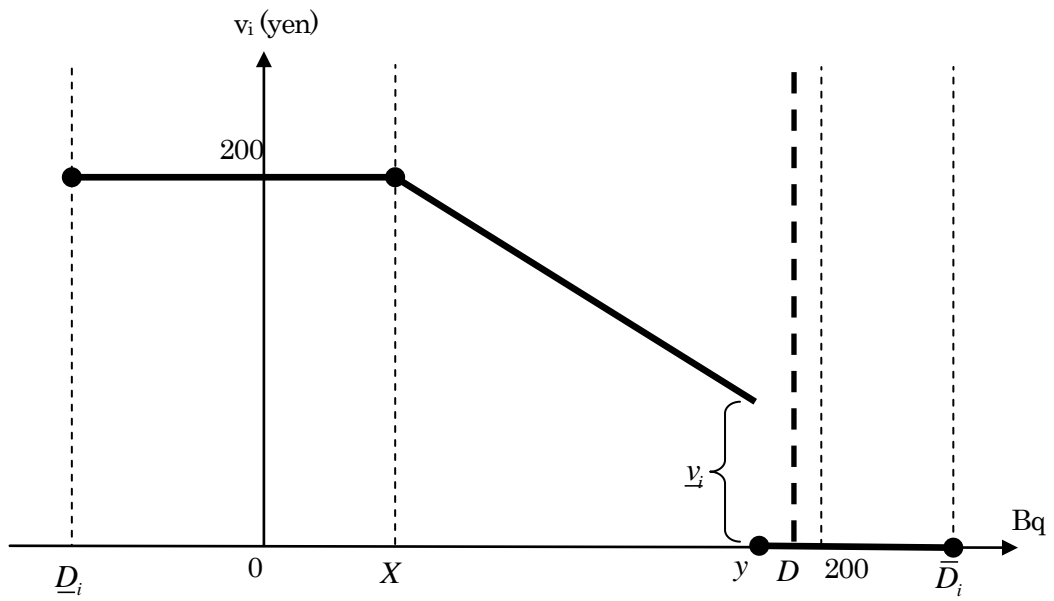
Figure 3-2: Case 2, $0 < v_i < 200$ Figure 3-3: Case 3, $v_i = 0$ 

Figure 4-1: Numerical examples

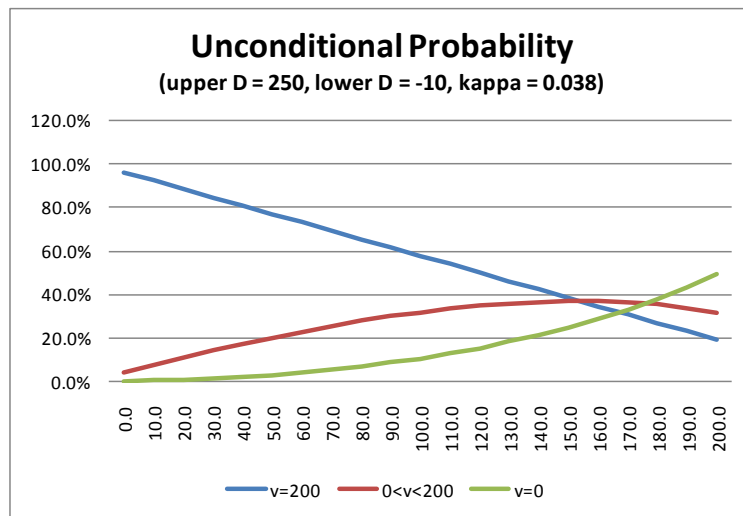


Figure 4-2:

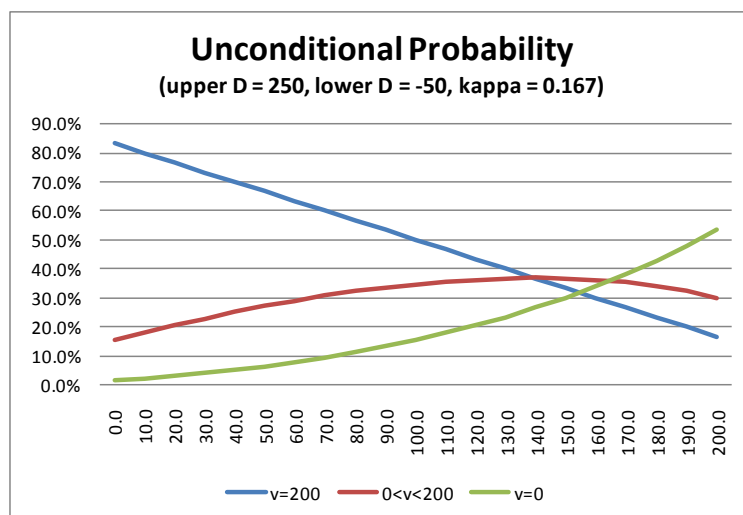


Figure 4-3:

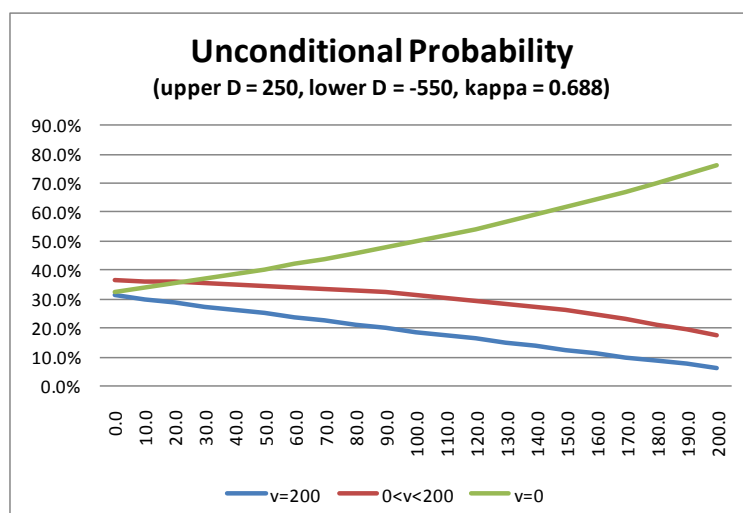


Figure 5-1:

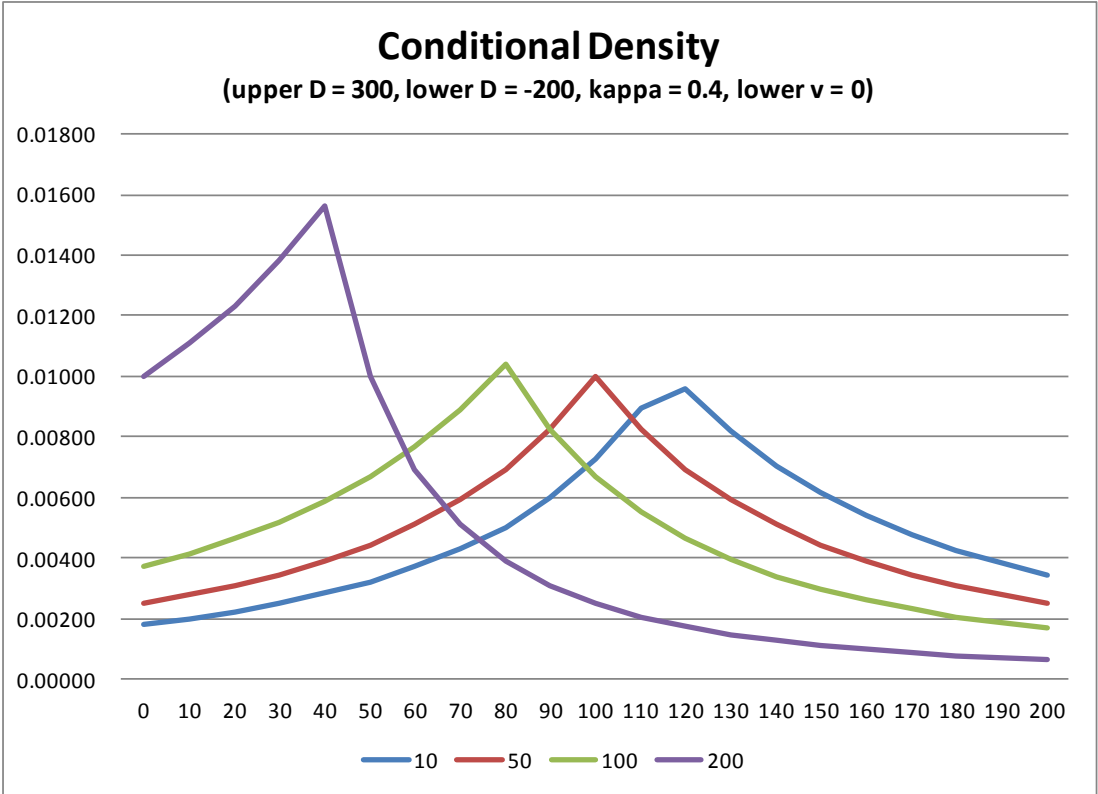


Figure 5-2:

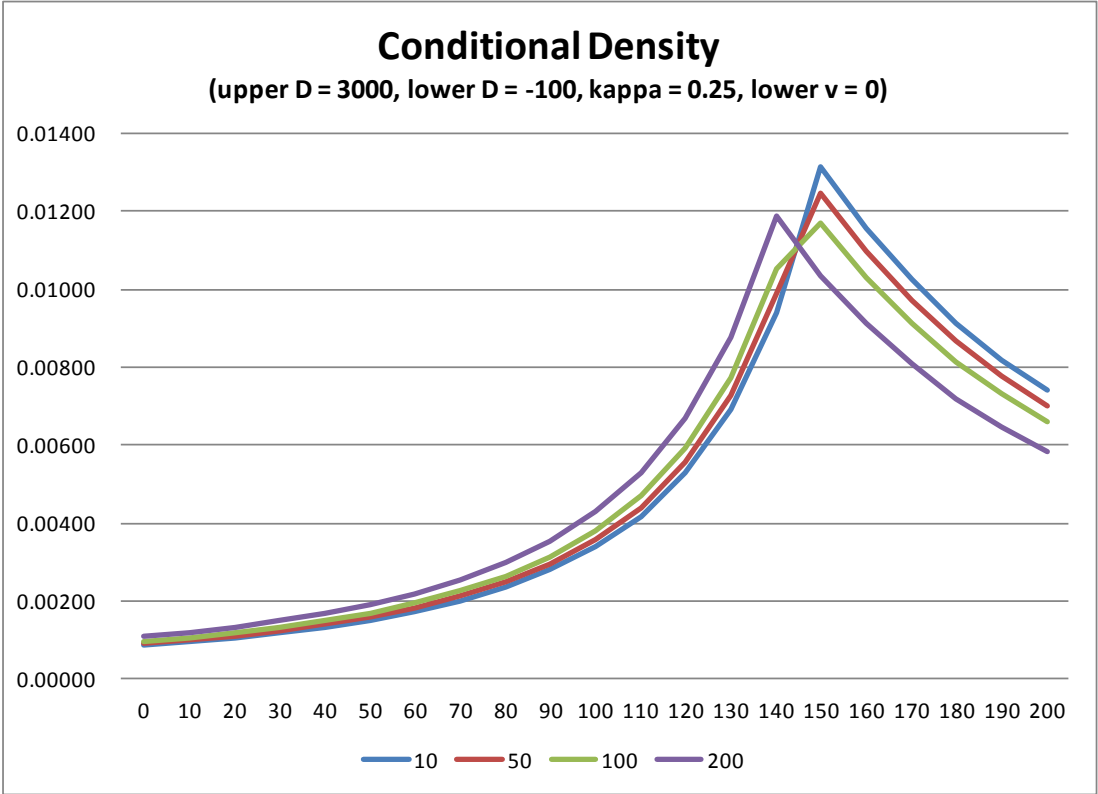


Figure 6-1: Lower upper limit of the valuation (v_i) with two observations included in Case 2

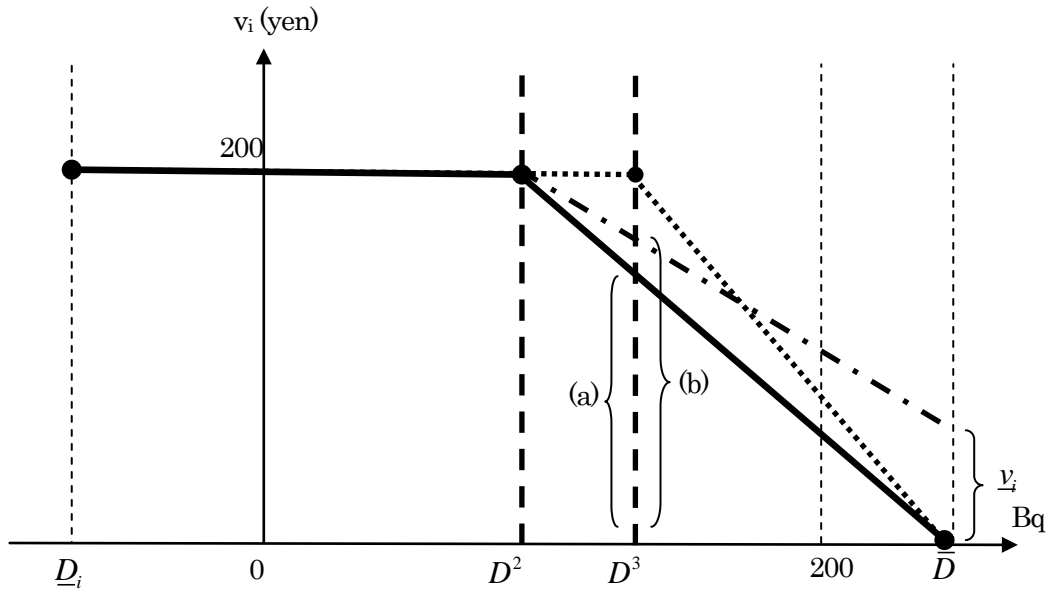


Figure 6-2: Higher lower limit of the valuation (v_i) with two observations included in Case 2

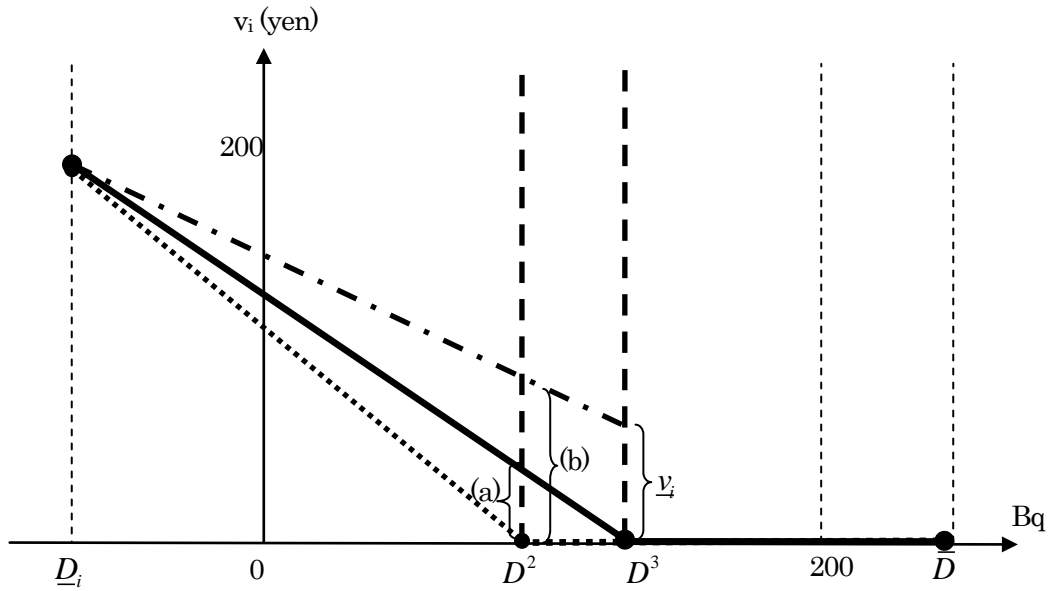


Figure 7-1: A shape of a density function of measurement errors (linear functions)

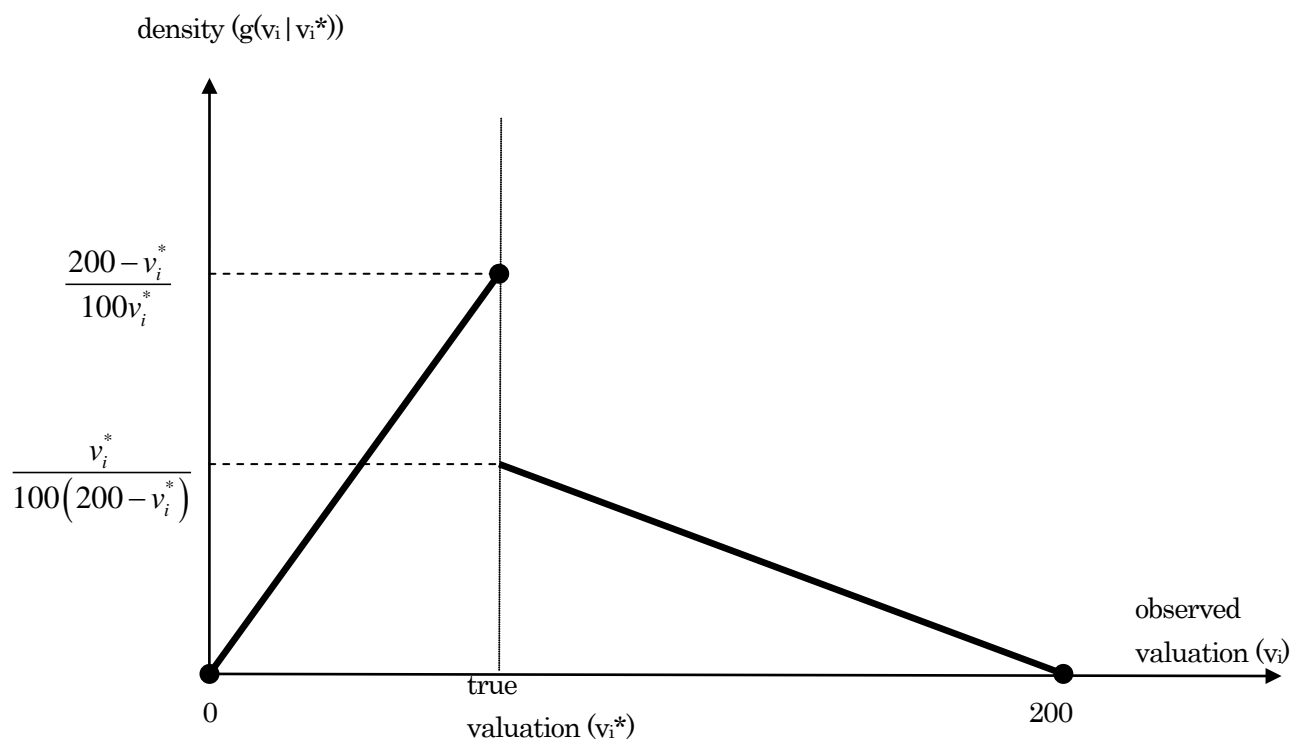


Figure 7-2: A shape of a density function of measurement errors (uniform distributions)

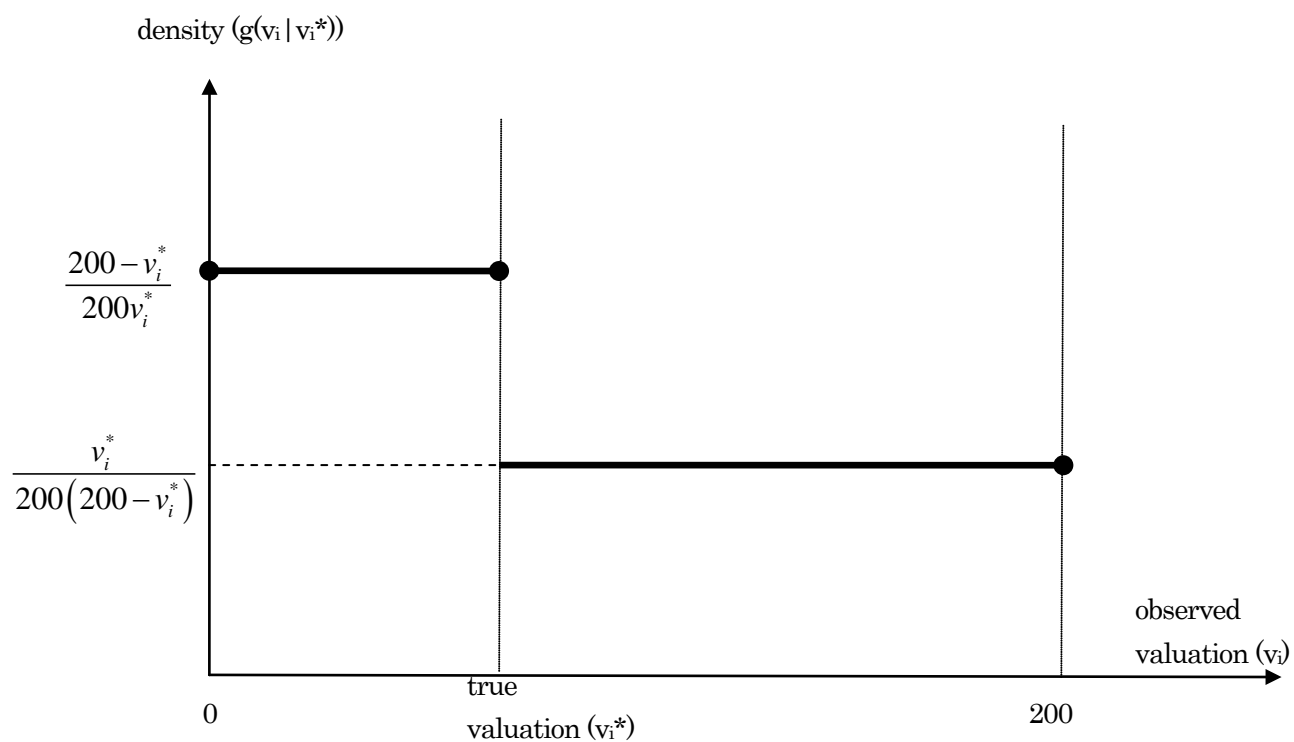


Figure 8-1: Histograms of the distribution of quoted discount prices at 10-yen intervals

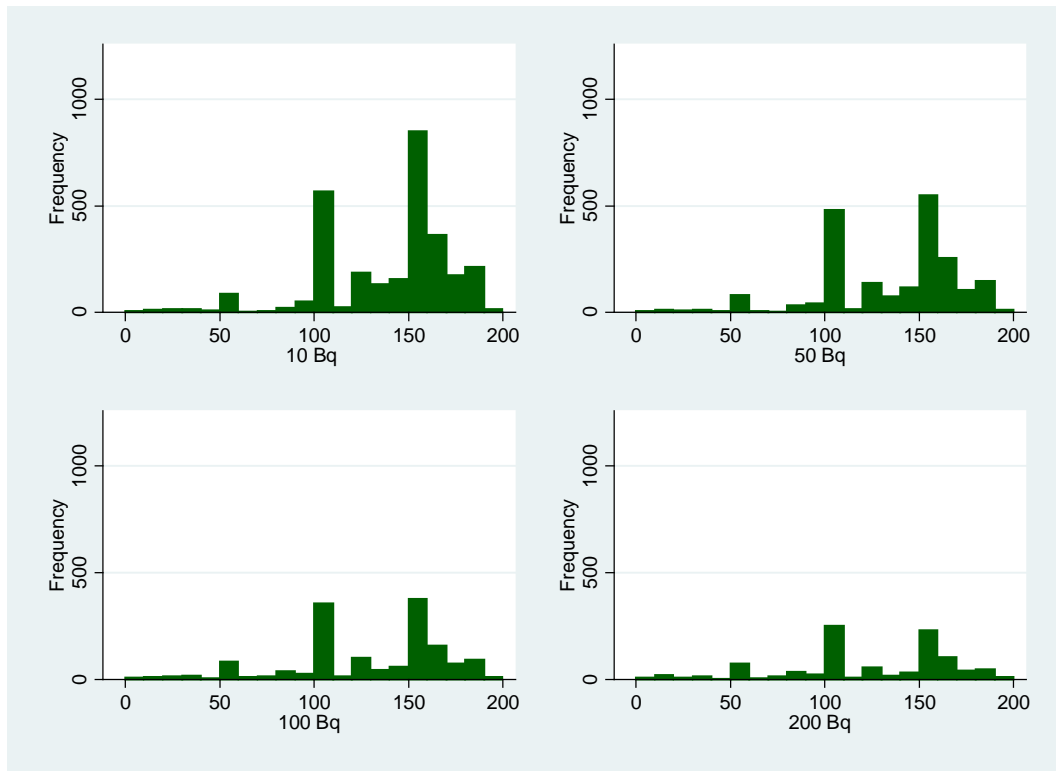


Figure 8-2: Histograms of the distribution of quoted discount prices at 50-yen intervals

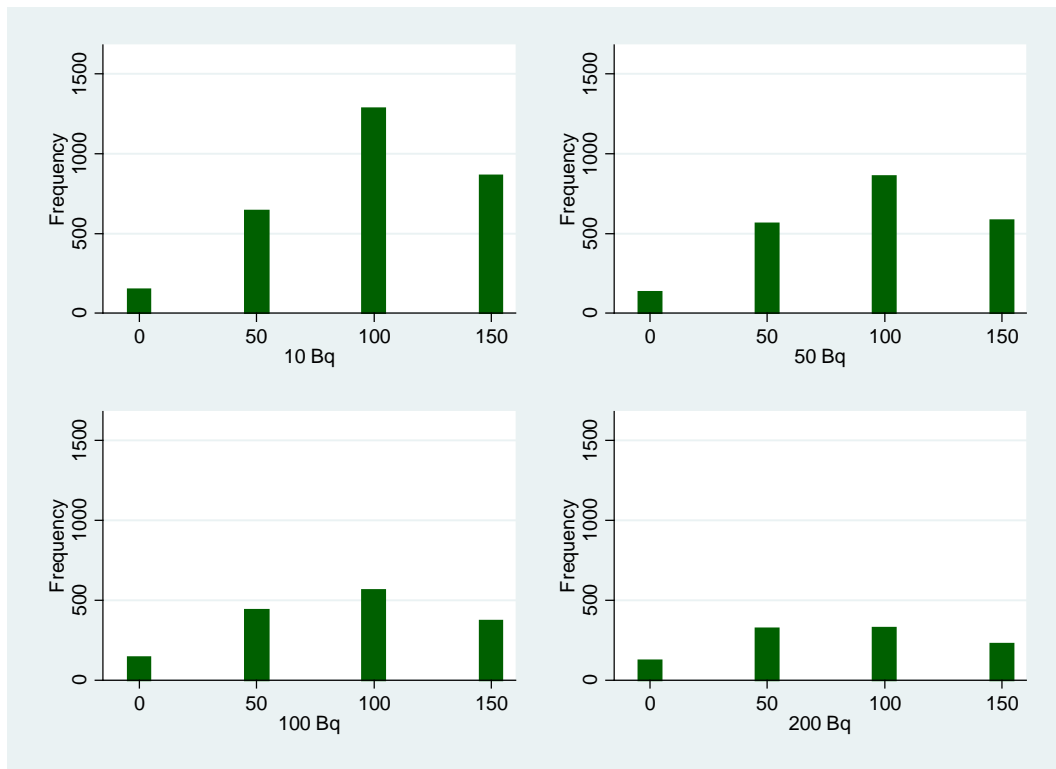


Figure 9-1: Histograms of the distribution of quoted discount prices at the highest contamination level in Pattern 4, 7, 8, 11, 12, and 13

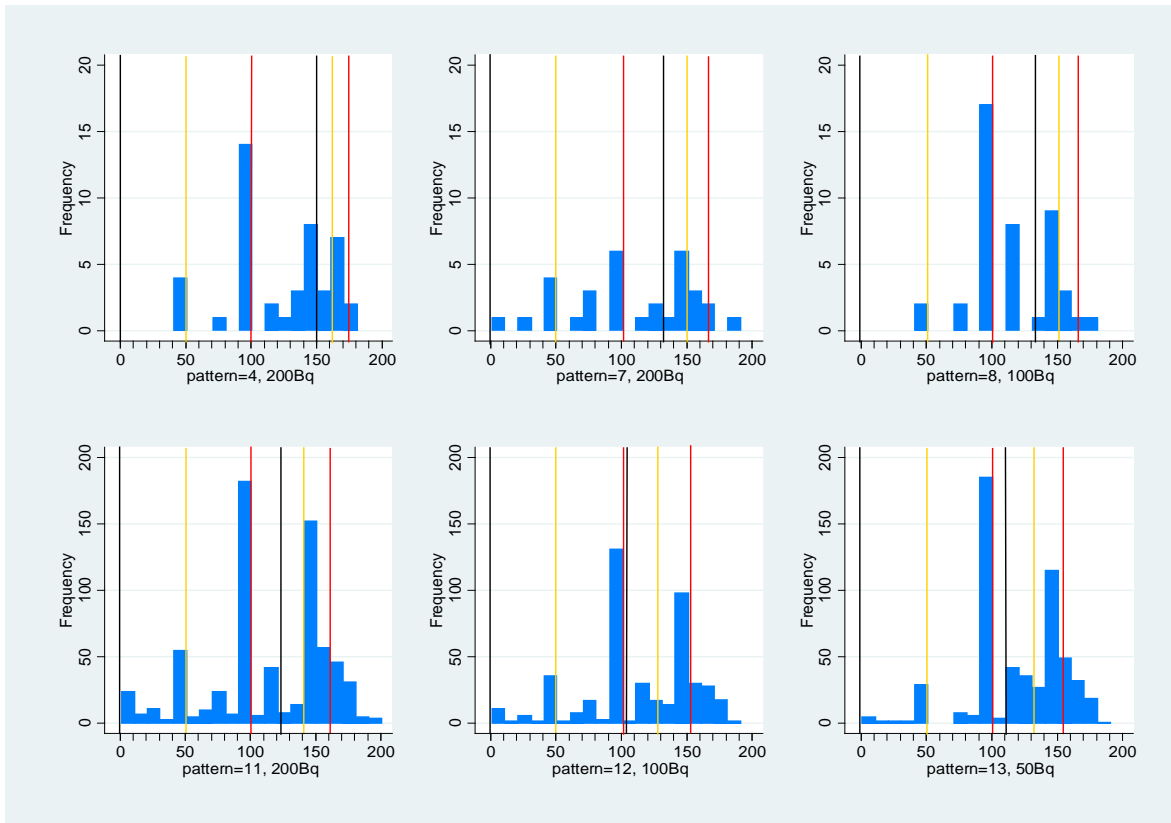


Figure 9-2: Histograms of the distribution of quoted discount prices in Pattern 2, 5, 9, and 14

