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Pesticide Residue Risks, Produce Choice, and Valuation of Food Safety: A Random Utility Approach

Food safety has received increased attention as a major consumer concern in recent years. Yet consumers seem to evaluate food safety risks differently from scientific experts (Kramer). This disparity in the public perceptions of food-related health risks has implications for both the design of policies to respond to concerns about food safety and the interpretation of the consumer behavior that is used to estimate the monetary value of those policies. In the policy context, *risk* has been used to describe probabilities of detrimental health outcomes from exposure to environmental pollutants (such as wastes, residues, and contaminants). The source of risk emphasized in this paper arises from exposure to pesticide residues on fresh produce.

Evidence from currently available consumer studies provides at best mixed judgments about how consumers respond to food safety risks. Several consumer studies found consumers' avoidance of certain foods in response to information about food contamination or dietary diseases in actual market-based situations (Swartz and Strand; Smith, van Ravenswaay and Thompson; van Ravenswaay and Hoehn (1991a); and Brown and Schrader; Capps and Schmitz). More recent studies reported consumers' willingness to pay higher prices for residue-free produce in both actual and hypothetical market situations (Hammitt; van Ravenswaay and Hoehn (1991b); Conklin, Thompson and Riggs). However, empirical evidence is not all encouraging in measuring the links between perceptions and behavior. Chalfant and Alston demonstrated that food consumption patterns did not appear to be influenced by health concerns. Ott, Huang and Misra also indicated that a majority of respondents surveyed in Georgia continued to practice their produce purchasing habits despite high perceived risks from pesticide residues.

An important feature of these early efforts to understand consumer demand for food safety was their focus on situations where we can assume consumers make continuous choices of risk differentiated produce. As a result, analysts can assume that they make marginal adjustments to reduce risks. Examples of those types of approaches include Becker's household production model and Lancaster's product characteristics model (see Smallwood and Blaylock for a review). Equally important, these studies generally failed to incorporate individuals' risk perception processes into their economic behavioral models. Consumers were assumed to know technical estimates of risk or to accurately perceive the risks in response to news coverage of food risks. Unfortunately, the objective measure of risks is not known exactly, even by scientific experts (Talcott). Moreover, the risk perception literature has repeatedly suggested that individuals seem to have difficulties dealing with low-probability events such as pesticide residue risks (Slovic, Fischhoff and Liechtenstein; Magat, Viscusi and Huber; Camerer and Kunreuther).

To address these issues--perceptions, behavior, and valuation--systematically, this paper develops a theoretical model integrating consumers' risk perceptions with their stated purchase behavior in response to scientific information about pesticide residue risks. Departing from the traditional food demand analyses, purchase decisions for fresh produce in the presence of risks are described as a discrete choice in a constrained expected utility maximization framework. Risk perception processes are specified using Bayesian learning models and are incorporated into the discrete choice model. A random utility model is derived from this utility-theoretic framework and then is used to measure price increments for reductions in risk.

The feasibility of the discrete choice model is illustrated using a pilot survey data that elicited contingent produce choices in a hypothetical market. Following the description of the collection procedures for the data, the next sections present empirical results of the discrete choice models and risk-price tradeoffs implied by the stated preferences for safer produce. The final section provides a brief summary and some explanations for major results.

Modeling Consumers' Stated Preferences for Safer Produce

Ex Ante Indirect Utility Function

Consider first a consumer's fresh produce purchase decision in the presence of pesticide residue risks. Suppose a representative consumer allocates his or her given income over fresh produce, X, and a Hicksian composite good, Z. While the consumer can observe some attributes of fresh produce (such as color, size, uniformity of shape, or freshness) prior to purchase, the individual cannot observe the amount of pesticide residues that might remain on the fresh produce.

For simplicity of analysis, the consumer is assumed to face only two-states of the world: either the occurrence or non-occurrence of adverse health outcomes.[1] If the consumer is exposed to pesticide residues over his or her lifetime, there is the probability of π that an adverse health event occurs. In addition, the consumer is assumed to evaluate the fresh produce that he or she consumes differently depending on the health outcome, implying state-dependent preferences (see Cook and Graham). Thus, the consumer's state-dependent utility functions can be defined as $U_c(X,Z)$ associated with the occurrence of the health event, and as $U_{nc}(X,Z)$ for the non-occurrence of health event.

Given the above assumptions, the consumer's purchase behavior can be described as maximizing the following expected utility subject to a budget constraint:

$$\max \quad EU = \pi U_c(X,Z) + (1-\pi)U_{nc}(X,Z) \tag{1}$$

$$\text{s.t.} \quad Y = pX + Z \tag{2}$$

where Y is income, and p is the relative price of X in terms of Z.

Solving the constrained expected utility maximization problem, defined in equations (1) and (2), yields an expected value of state-dependent indirect utility functions:

$$EV(p,\pi,Y) = \pi\, V_c(Y,p) + (1-\pi)\, V_{nc}(Y,p) \tag{3}$$

where $V_c(Y,p) = U_c(X^*(Y,p),\ Y\text{-}X^*(Y,p))$,
$V_{nc}(Y,p) = U_{nc}(X^*(Y,p),\ Y\text{-}X^*(Y,p))$, and
X^* denotes an optimally chosen level of the commodity X.

The state-dependent indirect utility functions in equation (3) are assumed to be well behaved and to satisfy the usual properties such as non-decreasing in Y and convexity in p (i.e., $\partial V_i/\partial Y > 0$ and $\partial V_i/\partial p < 0$, i=c,nc). The consumer makes purchase decisions about fresh produce before he or she realizes any adverse health effects due to pesticide residues. Therefore, the expected value of the state-dependent indirect utility function defined as equation (3) represents an ex ante indirect utility function (see Choi and Johnson; Smith and Desvousges, 1990).

Modeling Risk Perceptions

Most economic analysis using the expected utility framework has maintained that risk, π, is an "objective" probability. In other words, consumers are assumed to know or understand the technical estimate of risk. There is, however, a growing body of evidence indicating a divergence between consumers' perceived risks from environmental sources (including pesticide residues), and scientific experts' technical estimates of these risks (Slovic, Fischhoff and Liechtenstein).

Viscusi (1989) recently developed the prospective reference model that explicitly incorporates consumers' risk perception processes into the expected utility framework. He used a Bayesian updating model to explain how consumers process new information and revise their risk perceptions. The Bayesian updating rule implies that consumers' risk perceptions at a given point in time are a weighted average of prior beliefs about uncertain events and "sample" risk inferred from new information (either provided to or acquired by the consumers). In this perspective, the "risk" term in equation (3), π, can be replaced with a risk perception function as defined by equation (4):

$$\pi = \alpha_b \pi_b + \alpha_s \pi_s \qquad (4)$$

where π_b represents a consumer's prior perceived risk and π_s represents a technical estimate of health risk provided by experts. The weights, α_b and α_s, in equation (4) capture the consumer's evaluation of the relative precision of an underlying distribution of the process that generates the risk.[2]

A Random Utility Model Describing Contingent Discrete Choices for Safer Produce

Given the limited availability of risk-differentiated produce at food stores, it may not be feasible to observe consumers' marginal purchase decisions as the expected utility maximization framework (equations (1) and (2)) would envision. Alternatively, consumers' responses to risks from pesticide residues could be considered to be outcomes of a discrete choice decision process. Suppose that the consumer was offered two types of fresh produce that differ only in their prices and health risks. One, labeled as Type I, describes a produce item grown conventionally using pesticides. The other, labeled as Type II, describes another produce item grown the same way but tested for pesticide residues. The consumer's decision about which type of produce to choose entails a corner solution in which he or she makes a choice of <u>either</u> Type I <u>or</u> Type II produce. In this discrete choice model, the choice outcome is assumed to depend on the <u>total</u> expected utility that would be realized from consuming each produce type--Type I or Type II produce. In other words, the ex ante indirect utility, EV, is the maximum of the two <u>conditional</u> ex ante indirect utilities (EV^I and EV^{II}), as written in equation (5).

$$EV(M,p^I,p^{II},\pi^I,\pi^{II};S) = \max\,[EV^I(M,p^I,\pi^I;S),\ EV^{II}(M,p^{II},\pi^{II};S)] \qquad (5)$$

$$\pi^I = \alpha_b\,\pi_b + \alpha_s\,\pi_s^I \qquad (4\text{-I})$$
$$\pi^{II} = \alpha_b\,\pi_b + \alpha_s\,\pi_s^{II} \qquad (4\text{-II})$$

where p^I and p^{II} designate per-unit prices of Type I and Type II produce,
π^I and π^{II} denote health risk perceptions revised after receiving information about technical estimates of risk from consuming Type I and Type II produce (π_s^I and π_s^{II}),
S denotes a vector of attitudinal and demographic characteristics.

Because the potential health risks from consuming Type I produce are assumed to be higher than those from consuming Type II produce (i.e., $\pi_s^I > \pi_s^{II}$), holding other attributes of the two commodities constant, the price of Type I produce, p^I, is lower than the price of Type II produce, p^{II}. Equally important, the attitudinal and demographic characteristics variables, S, represent either individuals' state-dependent preferences associated with the adverse health outcome or their preferences for each type of fresh produce.

Note that the "extensive " margin of choice described as equation (5) does not require the analyst to observe information about the quantity demanded for a chosen type of produce, compared with the widely used shifts in demand approach (e.g., Swartz and Strand; Smith, van Ravenswaay and Thompson). In this discrete choice situation, consumers' avoidances of exposure to pesticide residues are simply reflected in their decisions to purchase Type II.

Following McFadden, we assume that each EV^i ($i=I,II$) is not completely known to the analyst and, therefore, is treated as a random variable. The unobservable elements could be individual-specific preference factors or alternative-specific produce attributes. From this perspective, the consumer would express his or her intention to purchase Type II only if

$$EV^{II}(.) = \overline{\overline{EV}}^{II} + \epsilon^{II} > \overline{\overline{EV}}^{I} + \epsilon^{I} = EV^{I}(.) \tag{6}$$

or

$$\Delta\overline{\overline{EV}} = \overline{\overline{EV}}^{II} - \overline{\overline{EV}}^{I} > \epsilon^{I} - \epsilon^{II} \tag{6'}$$

where $\overline{\overline{EV}}^i$ is the deterministic component of ex ante indirect utility function for choice i, $i=I,II$
ϵ^i is the unobservable stochastic component of EV^i for choice i, $i=I,II$.

One can further assume that ϵ^i is independently and identically distributed with a standard normal distribution. In this way, EV^i is structured as a random utility model introduced by McFadden and elaborated upon by Hanemann. This specification implies that a probit model will describe the consumer's purchase intention for Type II (safer produce).

Extending the conventional practice of specifying indirect utility functions (see Hanemann), the conditional ex ante indirect utility function for each type of produce (EV^i, $i=I,II$) was approximated to take a <u>linear</u> functional form (see Smith and Desvousges, 1990). Thus, the ex ante indirect utility difference function in equation (6') can be formulated as equation (7).

$$\Delta\overline{\overline{EV}} = \kappa - \gamma(p^{II}-p^{I}) + \nu(\pi^{I}-\pi^{II}) + \tau Y + dS \tag{7}$$

where $\kappa = \kappa^{II} - \kappa^{I}$, an alternative-specific constant,
$\tau = \tau^{II} - \tau^{I}$, $d = d^{II} - d^{I}$.

The coefficients of alternative-specific variables (prices and risk perceptions), γ and ν, were assumed to be the same for each of the conditional ex ante indirect utility functions, whereas the coefficients of individual specific variables (income and demographic factors), τ and d, were assumed to be different (Cramer, chapter 10). These specifications reflect an implicit assumption that marginal utilities realized from alternative-specific variables are the same regardless of consumers' purchase intentions for either Type I or Type II produce, but that individuals' socio-economic variables might contribute to the marginal utilities differently depending on whether consumers decide to purchase Type I or Type II. Equally important, the alterative-specific constant, κ, captures all other factors that might influence the difference in expected utilities but were neglected by analysts in the specification of conditional ex ante indirect utility functions.

Plugging equations (4-I) and (4-II) into equation (7), the ex ante indirect utility difference function can be modified to equation (8) (see Viscusi, 1989 for a continuous choice case).

$$\Delta\overline{E}\overline{V} = \kappa - \gamma(p^{II}-p^{I}) + \lambda(\pi_s^{I}-\pi_s^{II}) + \tau Y + dS \qquad (8)$$

where $\lambda = \nu\alpha_s$. Because the consumer's prior risk perception, π_b, in equations (4-I) and (4-II) was formed before receiving our questionnaires, the prior perceived risk would not affect the contingent choices, and canceled out in the process of calculating the utility difference function. This specification of the discrete choice model implies that consumer purchase decisions on safer produce (Type II) can be explained by their tradeoffs between price increase ($p^{II}-p^{I}$) and risk reduction ($\pi_s^{I}-\pi_s^{II}$). Unfortunately, the reduced form specification in equation (8) does not permit to recover the relative weight that the consumer placed on technical risk information, α_s, separately.

Survey Design and Data

The pilot data to implement the discrete choice model were collected by a survey technique creating a hypothetical fresh produce market.[3] Because of the complexity of the hypothetical commodity involved, health risks, an in-person survey would be a preferred method to achieve more accurate answers and high response rates (Mitchell and Carson, chapter 5). Unfortunately, limited resources prevented us from adopting those types of survey instruments and a mail survey method was chosen. Following Dillman's suggestions, the data collection procedures focused on improving key elements of questionnaire design such as relevant and understandable wording, question order that would reduce any bias, and layout and arrangement of questions conducive to accurate and easy answering. However, to facilitate the identification of primary decision makers for food shopping and the collection of market price information for produce items, survey questionnaires were distributed at the point of sale in the Raleigh/Cary area, North Carolina, instead of being mailed. As a result, we made some modifications to Dillman's Total Design Method (TDM).

The target population consisted of all households in the Raleigh/Cary area. Survey questionnaires attached with a cover letter and a self-addressed envelope were distributed to 1860 shoppers by 5 trained-interviewers at the entrance of 24 grocery stores during September and October 1990. This distribution technique did not allow us to send follow-up mailings because of our inability to obtain shoppers' names and addresses. Equally important, among 34 food stores from 7 major food chains in the Raleigh/Cary area which were identified and contacted for permission to distribute the questionnaires, internal policies of 10 food stores (from 2 food chains) did not allow us to undertake any survey activity at their stores. Excluding those who regularly go to shopping at one of the 10 food stores from the survey population is likely to introduce a sampling bias.

A total of 567 questionnaires were returned for a response rate of 30.5 percent.[4] About 70 percent of shoppers who accepted our questionnaires failed to return them. Therefore, it should be also recognized that this high "unit nonresponse" rate could result in nonresponse bias (Mitchell and Carson, chapter 12). Table 1 indicates that the demographic characteristics of the sample appear to be comparable with those of the target population. However, it is notable that female respondents were more dominant in our sample (69 percent) than in the *census* study (52 percent). Since our questionnaires were distributed at the point of purchase, it is more likely to be accepted by the persons who shop regularly for their households.

The survey collected information on consumers' expenditures on all food and on 23 individual produce items, contingent choices, subjective attitudes toward risks from pesticide residues on fresh produce, and economic and demographic information. This paper analyzes a subset of information collected from the survey, primarily the contingent discrete choice information.

The existing literature does not provide a clear-cut judgement on how best to elicit consumer risk perceptions and how to explain risk information to consumers. Therefore, our survey design process focused on developing a set of procedures that could effectively explain both the choice to be made and the levels of and changes in risks realized by produce choices. As a part of these efforts, two focus group sessions were conducted in Raleigh during March and May 1990. The first focus group participants were recruited from members of a Food Co-op by way of identifying "those population segments that are going to provide the most meaningful information" (Morgan, chapter 4). The six participants were asked to discuss and to evaluate the context of hypothetical choice situations used to describe changes in risk and price, the format used to explain risks from exposure to pesticide residues, actual fresh produce consumption patterns, and the attributes of produce that are important in purchase decisions (see Eom 1990 for details). During the two-hour session, two observers (graduate students) made as detailed notes as possible of each response. In addition, three tape players recorded the whole session. A transcript was written based on the tape recording, notes, and a review conducted right after the session.

Among several topics discussed, participants were given five choice tasks varying the way in which the price and risk attributes were presented: binary choice in price or risk, continuous choice in price or risk, and binary choice of preparation method. After participants having a chance to look them over, the moderator asked for their reactions: Could you answer these types of questions? Could you compare tasks and tell which one is easier or harder to answer? In response to these questions, each respondent stated his or her opinion. Several respondents stated that binary choices were easier to answer than continuous choices for either price or risk, and comparing risks were more difficult than comparing prices. Eight participants for the second focus group were recruited by a systematic random digital dialing process using the Wake County (NC) phone directory. The participants, who might more closely correspond to the sample population, evaluated the materials that were modified after the first session and reacted to the choice format in a similar manner to those of the first group.

Based on a qualitative and descriptive analysis of participants' comments along with direct quotes, we, as researchers, interpreted that the binary choice format seemed to provide a choice environment similar to actual selection processes for fresh produce at food stores.[5] Hence, a binary choice format using two produce labels was chosen to represent two types of fresh produce having different levels of price and risk. One type of produce, labeled <u>Type I</u>, is commercially grown and potentially contains pesticides. The other type, labeled <u>Type II</u>, is subject to more stringent tests for pesticide residues before being delivered to stores. Then each respondent was asked to compare the paired produce labels and to state his or her intention to purchase <u>either</u> Type I <u>or</u> Type II produce.[6] If respondents chose "neither" type of produce, they were asked to explain their reasons for doing so.[7]

An experimental design was used to vary the two end points (reference and target levels) and increments of risk and price attributes conveyed by the two produce labels. For the risk attribute, fourteen different risk levels were assigned to Type I produce, ranging from 3 additional cancer cases per 50,000 to 50 cases per 50,000 consumers over their lifetimes. Another fourteen risk levels were assigned to Type II produce, ranging from 1 cancer case per 50,000 to 30 per 50,000. These risk levels for both produce types were based on estimates defined by the National Academy of Science (NAS), 3/10,000, and EPA studies, 1/50,000. The risk reductions realized by switching from Type I to Type II produce ranged from 2 cases to 40 cases per 50,000 consumers. These sufficient variations of risk design points were judged to be important for two reasons: (1) Technical risk estimates (either from NAS or EPA) are not known with certainty. (2) the specific values of risk may affect how households process information about risks (see Smith and Desvousges, 1987).

In addition, respondents' subjective attitudes toward health risks from exposure to pesticide residues were measured on a 1 to 10 Likert scale--with 1 implying "no risk" and 10 implying "very serious risk".[8] Although the elicited responses may represent the intensity of respondents' feelings about health hazards due to pesticide residue exposure, the linear scale does not measure the exact probability of a health outcome. Possibly, respondents may have been thinking about more than the probability of the health outcome in answering the question. Viscusi and O'Connor acknowledged that the seriousness index might reflect an individual's beliefs about both the probability of adverse health outcomes and their severity. van Ravenswaay and Hoehn (1991b) found that consumers seemed to perceive risks of multiple health problems (such as allergies, heart disease, nervous system disorder and impaired immune system as well as cancer).

Another important issue raised from the focus group discussions involves the "commodity" specification. The focus group participants did not provide a strong consensus about whether to use a "typical" fresh produce item or a "particular" item in the contingent transactions. Reflecting this diversity, our survey questionnaires used two different elicitation methods to characterize the produce item evaluated and its prices (see Eom 1992 for details). In the contingent behavior questions in yellow booklets, each respondent was asked to identify a "specific" produce item that his or her family enjoyed the most during last summer and to fill in its per-unit price as price for Type I produce. The prices for Type I produce given by respondents ranged from $0.39 to $1.49. Subsequently, each was asked to fill in the price of Type II produce by adding a given price increment (one of four increments--$0.10, $0.40, $0.70 or $0.90) to the per-unit price of the chosen produce item.[9] In the contingent behavior questions in grey booklets, respondents were asked to evaluate a "representative" fresh produce item whose prices (for both Type I and Type II) were directly assigned by researchers. The price range for Type I produce corresponded to the actual prices of 23 produce items in the Raleigh/Cary area, ranging from $0.49 to $1.19. Despite different unit-price specification methods for Type I and Type II produce, the same price increments were assigned for both commodity specifications. Table 2 defines selected variables used in this analysis and provides some summary statistics.

Empirical Results of Price and Risk Tradeoffs

In response to the survey question eliciting a contingent discrete choice, 276 respondents were able to make the contingent choice of either Type I or Type II produce and provided consistent responses across different questions. This subset of the sample was used to estimate the discrete choice model. While the "neither" choice option in the contingent behavior question was introduced to more closely simulate the actual produce purchase situations, dropping those who did not make discrete choices could introduce a selection bias. To account this bias, a bivariate probit model was developed to simultaneously determine factors influencing decisions on making the contingent choices (either Type I or Type II) and those influencing decisions on making Type II choices. Appendix A reports estimates of bivairate probit models with sample selections, which suggest no apparent sample selection effects--at least for the price and risk variables.[11] Of the subsample used for this analysis, a majority of consumers (about 65 percent) expressed willingness to purchase the more stringently tested produce (Type II) even though Type II produce costs 35 cents more on average.

Table 3 reports the probit estimates for the discrete choice models to explain factors affecting consumers' intentions to purchase safer produce (Type II). Three alternative specifications for models broadly consistent with equation (8) varied the way in which the risk variable was included. The next column of each model specification presents average values of marginal effects of several key variables on the probability of choosing Type II produce. Model (A) represents a direct estimation of equation (8), in which the formulation of risk perceptions was derived from a Bayesian updating model. Models (B) and (C) are derived based on the assumption that individuals' risk perception processes are more complicated than what we can postulate with a simple Bayesian model. For example, several previous studies (Smith and Johnson; Ippolito and Mathios; Kenkel; Viscusi, 1991) suggested that individuals' information processing abilities might depend on some individual characteristics (such as attitudes toward the event at risk, age and education). To incorporate this possibility, the parameter associated with individuals' information processing, λ, varied with those individual-specific variables in models (B) and (C).[12]

Comparing the effects of risk information across different models indicates that the technical risk information provided in the survey does not seem to affect consumers' purchase intentions for safer produce until we explicitly introduce subjective beliefs about the risk and demographic characteristics in risk perception processes. The coefficient of RISK REDUCTION variable in model (A) is not statistically significant, although it has the expected sign. Whereas, the SERIOUS-COMMERCIAL variable in model (A), which represents individuals' subjective attitudes toward pesticide residue risks, has a significant positive influence on the contingent discrete choice. Moreover, as the SERIOUS-COMMERCIAL and/or AGE and EDUCATION variables were interacted with the RISK REDUCTION variable in models (B) and (C), the RISK REDUCTION coefficients changed to be statistically significant with the expected signs.

On the contrary, the effects of price increase (p^{II}-p^{I}) have theoretically expected signs and are statistically significant across all the model specifications. As the price difference between Type II and Type I produce gets larger, given the amount of risk reduction, consumers are less likely to express purchase intentions for Type II produce. In other words, as predicted, consumers considered the newly introduced produce type (Type II) a substitute for the existing type of produce (Type I). Equally important, differences in knowledge about general science (reflected in schooling) appeared to influence how respondents interpret information about pesticide residue risks (see also Kenkel;

Ippolito and Mathios). For example, better educated consumers were more reluctant to change purchasing behavior in response to risk information (presented with a form of low-probabilities). One possible explanation for this reluctance is that more educated people are usually well grounded in basic scientific principles (such as the concept of probability) or in understanding the uncertainty around scientific information about pesticide residue risks. Therefore, they are more skeptical about the benefits of small reductions in risks realized by switching to Type II produce.

However, consumer income levels did not have a significant impact on preferences for Type II produce, implying a constant marginal utility of a dollar regardless of choices. This evidence indirectly supports the assumption made for the coefficients of the prices of Type I and Type II produce (γ). Other individual characteristics such as age, sex, and number of children were also found to have little influence on decisions to purchase Type II produce. These insignificant effects of demographic variables may stem from the nature of the discrete choice decisions considered: the <u>one-time</u> choice of a fresh produce type without including any <u>quantity adjustment</u>.

In terms of overall performance of model specifications, model (A), despite the insignificance of the RISK REDUCTION variable, was judged to be 'best' performed compared with other models based on two measures of goodness of fit: pseudo R^2 and the proportion of correct prediction. To further investigate the appropriate specification for evaluating the effect of technical risk information on the discrete choice, a J test was constructed to determine the suitability of the theoretically consistent model specification (model (A)) against other non-nested variations (model B or C) (see MacKinnon, White and Davidson; Smith and Maddala). When model (A) was tested against model (B) or (C), we failed to reject the model specification in (A) over either of the competing models (with the test statistics of -0.210 and -0.135 respectively). However, either model (B) or (C) was tested against model (A), we rejected these models in favor of model (A) at the significance level of 1% (with the test statistics of 5.119 and 3.902 respectively). The results of J test confirm that model

(A) contains a preferred set of independent variables for estimating the discrete choice models, suggesting that technical risk information may not be a significant determinant for the contingent discrete choices.

Measuring Price Increments for Risk Reductions

Using estimates of the ex ante utility difference function defined in equation (8), one can measure values of risk reduction that consumers would realize by switching to Type II produce. One of several possible measures of valuing risk changes is the per-unit price increment, ω, in addition to the price of Type I produce that makes consumers indifferent between purchasing Type I or Type II produce. From equation (6), the price increment associated with risk reduction, ω, is defined as an amount additional to the price of Type I produce that equates the two conditional ex ante indirect utility functions, yielding equation (9):

$$EV^{I}(.) = \bar{\bar{EV}}^{I}(Y,p^{I},\pi^{I},\theta) + \epsilon^{I} = \bar{\bar{EV}}^{II}(Y,p^{I}+\omega,\pi^{II},\theta) + \epsilon^{II} = EV^{II}(.) \qquad (9)$$

Although the price increment, ω, in equation (9) can be known as a fixed value for each consumer, it is considered a random variable by analysts for the same reasons given earlier. Following Hanemann's argument, this analysis employed the analyst's expectation of the ex ante indirect utility function to eliminate the randomness of the welfare measure (i.e., $E[EV^{I}(.)] = E[EV^{II}(.)]$).

To estimate the price increment, one can substitute the term $(p^{I}+\omega)$ for p^{II} in the linearized random utility model (equation (8)) and solve for the value of ω that makes the ex ante indirect utility difference function $(\Delta\bar{\bar{EV}})$ equal to zero for each consumer. That substitution yields equation (10):

$$\omega = \frac{\kappa + \lambda(\pi_{s}^{I}-\pi_{s}^{II}) + \tau Y + cW + dS}{\gamma} \qquad (10)$$

Equation (10) suggests that the consumer valuation of risk reduction, ω, will be increased as the amount of risk reduction $(\pi^{I}_{s}-\pi^{II}_{s})$ gets larger.

Before calculating the price increment for risk reduction, one important issue must be clarified in relation to the amount of risk change to be valued. Respondents in our survey were assigned randomly to one of fourteen different combinations of risk associated with Type I and Type II produce, which implies that each consumer is evaluating a different level of risk reduction. To address this issue, six scenarios of "representative" risk change were selected based on the two technical estimates of risk that may be potentially relevant to EPA's tolerance standard decisions. The risk level estimated by NAS, 3/10,000, was treated as the upper bound of risk changes and the risk level estimated by EPA, 1/50,000, was treated as the lower bound of risk changes. Then, three different risk changes (1/10,000, 10% and 50% risk reductions) were considered from the upper bound of risk (3/10,000) and to the lower bound of risk (1/50,000), resulting in six different combinations of risk reduction scenarios, as reported in the first two columns of Table 4. For each risk reduction scenario, the price of Type I produce was represented by the average price of Type I produce over the sample, \$0.88.

The last two columns of Table 4 report estimates of the average price increment for each scenario based on "better" fitted model specifications in Table 3 (i.e., models (A) and (C)). Price increments were calculated for each consumer and were averaged over the sample and the standard deviation of the estimated average price increments was also reported. Overall, consumers are willing to pay considerably more for the safer produce (Type II). In effect, compared to the average price of Type I produce, \$0.88, price increments for the six risk scenarios accounted for 85 to 90 percent increases in price from both models (A) and (C).[13]

One of the most striking features of the results is that estimates of price increments calculated using model (A), on average \$0.80, are significantly higher over the six risk reduction scenarios than those calculated using model (C), on average \$0.75.[14] Since the technical risk information in model (A) was not a significant determinant in explaining respondents' intentions to purchase safer produce, one would expect that price increments estimated using model (A) will be lower as well as little variation across six risk reduction scenarios. Furthermore, even when model (C), with the significant RISK REDUCTION variable, was employed to estimate price increments, the results do not seem to confirm the prediction from equation (10). While the amount of risk reduction realized by switching to Type II produce across the six risk reduction scenarios ranged from 10% to 83%, there is insignificant variation between the price increments estimated for the larger risk reduction (e.g., an 86 percent price increase for a 50 percent risk reduction) and those calculated for the smaller risk reduction (e.g., an 84 percent increase for a 10 percent risk reduction).

Summaries and Conclusions

This paper has developed a new approach for describing consumer preferences toward health risks posed by pesticide residues when consumption decisions must be made with incomplete information. Estimating demand for food safety requires a framework that recognizes the limited opportunities for observing responses to risks with market-based decisions. Unlike the existing studies that treat choices as marginal adjustments, the model developed here treats the choices involving pesticide residue risks as discrete. The model also incorporated individuals' learning processes in response to additional risk information as an integrated part of consumers' "rational" decisions.

Empirical findings from a pilot consumer survey support the existence of self-protective behavior. Respondents in our survey stated an aversion to pesticide-containing produce in a hypothetical market in the same manner that they avoided certain products in response to information about chemical contamination in actual markets. However, consumers' stated preferences for safer produce were primarily explained by price difference and the risk that consumers believe to be associated with the pesticide residue exposure, not technical risk information provided in the survey alone. In addition, individual characteristics reflecting their abilities to process technical risk information (such as education levels) were important in explaining individuals' risk perception processes and produce choices.

As indicated several times, the actual risks of exposure to pesticide residues are not well understood even by scientific experts. The controversy over scientific risk assessments was manifested by the Alar incidence in 1989. Since then, there has been a vast amount of publicity about health risks from exposure to Alar and other pesticide residues in food (see van Ravenswaay and Hoehn, 1991a). Reflecting the uncertain nature of technical risk estimates, however, there was no census about the actual risks of pesticide residues in food among different sources of information (e.g. government agencies versus consumer groups). Because of these highly publicized events, respondents might have perceived high risks from pesticide residues and also have developed attitudes of mistrusting technical risk estimates. Consequently, the new technical risk information provided in our survey did not provide much learning opportunities for the events at risk, resulting statistical insignificance of coefficients of new information in the Bayesian learning model.

The tendency to perceive higher risks for highly publicized events may partly explain the substantially high price increments for safer produce, which guarantees only very small risk reductions. This overestimation of low-probability events is consistent with behavioral patterns suggested in previous studies of individual decision makings in the presence of risks . Moreover, the respondents' awareness of sizable uncertainty (sometimes several orders of magnitude) about technical risk estimates could have induced the insensitivity of price premium across different risk reduction scenarios. The range of risk reductions considered (7.5/50,000 to 1/50,000) was quite small in absolute terms, and thus, may fall within the same margin of safety for each respondent. This view may offer one possible explanation for why the price increments estimated from model (C) with significant risk information effects were <u>not</u> larger than those from model (A) with insignificant information effects. What consumers evaluated in the survey was the difference in "food safety" implied by the two different types of produce rather than changes in "risk" per se. Therefore, consumers' high price premium may simply reflect their desires to assure that the food they eat is safe, rather than to ascertain particular amounts of risk reduction.

Of course, the empirical findings are subject to several caveats. First, our data recorded behavioral intentions to undertake protective behavior to reduce risks, which may not correspond fully to actual behavior observed in market transactions. Second, our study design focused on the tradeoffs between risk and price while holding other attributes (such as freshness, cosmetic appearance) constant. Finally, the sample used to estimate probit models is small and specialized. Certainly, these shortcomings require that the estimated risk-price tradeoffs be interpreted and generalized cautiously. Perhaps, consumers' responses to food risks including pesticide residues could be better understood with different survey methods, in which one could more accurately elicit consumers' risk perceptions <u>before</u> and <u>after</u> receiving risk information and more explicitly detect the dual role of self-protection (in the form of purchasing safer produce) and risk information on consumers' decisions to reduce health risk.

Footnotes

1. Based on Hammitt's study and the National Academy Science report (NAS), the possible health effects identified to date include cancer, neurological damage, birth defects and genetic defects. Therefore, the risks from exposure to pesticide residues are to be described by a pair of each health outcome and its likelihood, as Rescher has acknowledged. Nevertheless, this paper focuses on cancer risk partly because of better availability of technical estimates as well as the importance in view of public health. For example, the NAS study assessed additional cancer risk from life time exposure to 28 oncogenic pesticides (i.e., substances capable of producing benign or malignant tumors) that might remain on 15 common foods.

2. Viscusi (1989) characterized prior risk assessments by a beta distribution and treated sample risks as a sequence of Bernoulli trials. Smith and Johnson assumed independent normal distribution for both prior and sample risks.

3. The survey technique was previously applied to study individuals' behavioral intentions in situations involving risks. Much of the work is associated with Viscusi (Viscusi and O'Connor; Magat, Viscusi and Huber), and Smith and Desvousges (1987 and 1990).

4. Compared with previous contingent valuation studies which had no follow-up mailings, the response rate for our mail survey appears to be quite high. The response rate of previous studies was about 25 percent.

5. Although the focus group discussions provide an opportunity to listen how people feel, think and talk about food risks, pesticide residues and other related topics, they are inherently qualitative and thus can not provide valid statistical results (Morgan). Therefore, they should not be used a substitute for more systematic quantitative research. See Desvousges and Smith for a discussion of the use of focus groups in the design of surveys involving risks.

6. This elicitation method for the discrete choice can be viewed as a combination of the "take-it-

or-leave-it" (originally used by Bishop and Herbelein) and the "paired comparison" methods (used by Magat, Viscusi and Huber). This "either/or" choice format was similar to the conventionally used "take-it-or-leave-it" of yes/no choice in that it is also a binary choice. However, it asked respondents to compare two different alternatives--Type I and Type II--instead of giving a "yes/no" response for a single alternative. In contrast to the interactive nature of risk-dollar tradeoffs in the paired comparison approach, respondents' preferences between two types of produce were inferred from one-time contingent choice between the two types of fresh produce.

7. This "neither" option was included in the questionnaire because participants in the two focus groups repeatedly pointed out that the "either/or" option may not sufficiently explain all the alternatives that consumers can take to deal with the pesticide residue risks. Of the sample, 35 percent of respondents were not able to or refuse to make the contingent discrete choices. Eight percent of the sample said they would stop eating the produce item completely, and 11 percent said they would prefer organically grown produce. The remaining 16 percent said they did not agree with the information presented on the produce labels or were not able to evaluate the tradeoffs between risk and price (not sure what to do).

8. To assess the seriousness of certain sources of risks, researchers have used several means: a risk ladder, risk circle, a likert 1 to 10 scale, or a different orders of magnitude of chance. Among those elicitation methods, several earlier studies (Viscusi and O'Connor; Smith and Johnson; Smith and Desvousges, 1988) indicated that a 10-point linear scale offered simple and understandable means of elicitation with a sufficient range for perceived risks.

9. Respondents who answered yellow questionnaire booklets came up with 19 different produce items as their family's favorites. But none of the produce item was chosen by a majority of the respondents in the sample. This finding implies that if we had picked a "particular" produce such as apples to be evaluated in the contingent behavior question, then the sample size that can be used to

estimate the discrete choice model would have dramatically reduced. On the other hand, respondents who received yellow booklets might not evaluate the "representative" produce item that assigned to those who received grey booklets. As an attempt to resolve this issue, a Stone price index formula was used to consturct a price index for the "representive" fresh produce for those who answered yellow booklets:

$$\text{Log } p_i = \Sigma w_{ij}*\log p_{ij}j + (1-\Sigma w_{ij})*\log CPI_{FV} \qquad \text{(a)}$$

where p_i = Price index for ith respondents who received yellow booklets for the aggregate freh produce
w_{ij} = Expenditure share of ith respondent's total expenditure on fresh produce reproted for jth produce item. $j=1,\ldots,23$
Log p_{ij} = Natural log of price for jth fresh produce consumed by respondent i.
Log CPI_{FV} = Natural log of consumer price index for general fruits and vegetables during October 1990.

The construction of an aggregated price index was possible because our survey collected information on respondents' expenditures on 23 individual produce items as well as total expenditures on fresh produce. Actual retail prices of the 23 items were collected at 24 food stores before distributing the survey questionnaires. However, most respondents reported only a subset of the 23 items, and therefore the expenditure shares did not sum to 1. Thus, the second term on the right-hand side of equation (a) was included. The quality control scheme of the survey allowed us to match each respondent to a food store and prices of the 23 items at that particular store. Then, per-unit prices of "specific" Type I and Type II produce items reported by respondents with yellow booklets were substituted for actual prices of the same produce items.

11. In the sample, contingent discrete choices of Type II produce are observed only if the respondents decided to belong to the subgroup of contingent choice-makers (either Type I or Type II). Suppose that ϵ_1 denotes random disturbances associated with making the discrete choices of Type II produce and ϵ_2 represents random errors related to decisions on making contingent choices (either Type I or Type II). To account for this non-random selection effects, ϵ_1 and ϵ_2 are assumed to have a

joint bivariate standard normal distribution with correlation coefficients of disturbances being ρ (Amemiya). Comparing the results of the two discrete choice models in Appendix A to those of models (B)and (C) in Table 3, it appears that the overall effects of key determinants--price and risk--were not significantly distorted by restricting the sample to the contingent choice-makers. This finding and an estimate of positive ρ imply that characteristics of choice-makers may not be systematically different from those of non-choice-makers, and therefore the sample selection effect is not likely to be a crucial issue in generalizing the results of the probit models in Table 3 using choice-makers to the whole sample.

12. The specifications of models (B) and (C) are, in effect, *varying coefficient models* (see Kmenta, chapter 11; Brown and Schrader). The information-related coefficients, λ, in models (B) and (C) vary among individuals, while that in model (A) is fixed across observations. That is,

model (B): $\Delta\bar{E}\bar{V} = \kappa - \gamma(p^{II}-p^{I}) + \lambda(\text{SERIOUS-COMMERCIAL})(\pi_s^{I}-\pi_s^{II}) + \tau Y + dS$

model (C): $\Delta\bar{E}\bar{V} = \kappa-\gamma(p^{II}-p^{I})+\lambda(\text{SERIOUS-COMMERCIAL,AGE,EDUCATION})(\pi_s^{I}-\pi_s^{II})+\tau Y + dS$.

For simplicity, the individual-specific variables affecting risk perception processes did not overlap with those affecting their behavioral preferences (S) in each model specification. In other words, the SERIOUS-COMMERCIAL, AGE, EDUCATION variables were included as a subset of S in model (A), but not in model (C). To fully recognize possible differences in evaluation of the relative precision of technical information among consumers, the equation (8) could be specified as a *random coefficient model*. That is, the information related parameters can be substituted with their means plus disturbance terms (e.g., $\lambda^i = \lambda + e^i$ for ith individual). This specification will yield a heteroscedastic disturbance term and require to employ estimating procedures that will improve efficiency, compared with the estimator that will be employed in the following section (see Kmenta for detail).

13. The range of price increments measured in our analysis is within the range of the actual price premium for organic produce available in food stores. For example, Conklin, Thompson and Riggs

found that the retail price premium for eight organic fresh produce items ranged from 16 to 128 percent above corresponding conventional produce item prices in Tucson, Arizona area during 1991. Nonetheless, it is important to emphasize that our study is designed to test specific hypothesis regarding consumers' responses to risk information, but not to measure population estimates of consumer willingness to pay for risk reductions. Therefore, the price increments calculated using the probit estimates should be evaluated in terms of the direction, but not in terms of exact magnitude.

14. For instance, when we compare two sample means of price increments ($0.80 versus $0.76), the Z statistic is 2.86 at the 5% significance level, which suggests that price increments estimated using model (A) are significantly different from those estimated using model (C).

Table 1

Comparison of Sample Characteristics

	Target Population[a]	Sample
Income (in 1989)		
Mean	43470	47100
Per Capita	17540	18115
Age[b]		
Median	35.0	37.1
Education[c]		
Mean School Years completed	14.7	15.9
Sex		
Percent Female	51.5%	67.9%
Household Size	2.5	2.6

Source: The 1990 Census of Population and Housing.

[a] Target population is defined as individuals within the Raleigh-Cary standard metropolitan statistical area. All values of the target population are derived from the 1990 Census of Population and Housing.

[b] These populations include only those individuals 18 years and over.

[c] These populations include only those individuals 25 years and over.

Table 2.

Definitions of Variables and Sample Characteristics

Variable Names	Description	Mean	Standard Deviation
PRICE INCREASE	Difference between price of Type II and price of Type I produce	0.35	0.57
Version	Qualitative variable (0,1) = 1 if respondents received yellow color booklet	0.52	0.50
RISK I	The number of additional cancer cases over 50,000 people exposed by consuming Type I produce over their lifetimes	28/50,000	18/50,000
RISK REDUCTION	Difference between risk from consuming Type I and risk from consuming Type II produce	20/50,000	15/50,000
SERIOUS-COMMERCIAL	1 to 10 subjective seriousness index of health risk from commercial produce. The scale 1 implied "no health risk" and 10 implied "very serious risk."	6.6	2.1
RISK REDUCTION * RISK-COMMERCIAL	Interaction between RISK REDUCTION and RISK-COMMERCIAL	132/50,000	114/50,000
INCOME	Household's before tax 1989 annual income in thousands. Mid-points of 8 categories.	47.100	25.837
AGE	Age of household's member who filled in the questionnaire	37.1	12.5
EDUCATION	Years of education completed by the respondent	15.9	2.4
SEX	Qualitative variable (male = 0, female = 1)	0.68	0.47
NUMBER of CHILDREN	Number of children under 18 years old in each household	0.65	0.91
ASK DOCTOR	Attitudinal variable (0,1) = 1 if the respondent indicated that the statement "I always ask my physician many questions or regularly read articles about health" described himself or herself very well	0.30	0.46
SERIOUS-ORGANIC	1 to 10 subjective seriousness index of risk from consuming organic produce. The scale 1 implied "no health risk" and 10 implied "very serious risk."	2.8	1.8
SERIOUS-TESTED	1 to 10 subjective seriousness index of risk from consuming laboratory-tested produce. The scale 1 implied "no health risk" and 10 implied "very serious risk."	4.4	2.2

Table 3.
Probit Estimates for Purchase Intentions on Safer Produce

Independent Variables	Models (A)	M.E.[a]	(B)	M.E.[a]	(C)	M.E.[a]
Intercept	0.763 (1.058)		2.004 (3.160)		1.217 (3.901)	
Price Increase	-1.103 (-3.536)	-0.337	-0.959 (-3.314)	-0.326	-1.040 (-3.472)	-0.334
Version	-0.921 (-3.586)		-0.765 (-3.234)		-0.859 (-3.524)	
Risk Reduction	0.0006 (0.102)	0.0002				
Serious-Commercial	0.247 (5.583)					
Risk Reduction* Serious-Commercial			0.0018 (2.359)	0.004	0.0073 (4.355)	0.015
Age	0.0009 (0.125)		0.0008 (0.116)			
Age* Risk-Reduction					-0.0001 (-0.378)	
Education	-0.066 (-1.695)		-0.070 (-1.926)			
Education* Risk-Reduction					-0.0024 (-2.690)	
Income	0.0015 (0.418)	0.0004	0.0009 (0.259)	0.0003	0.0006 (0.189)	0.0002
Ask Doctor	0.068 (0.344)		0.191 (1.009)		0.156 (0.820)	
Number of Children	-0.119 (-1.258)		-0.083 (-0.926)		-0.122 (-1.336)	
Log (L)	-148.7		-162.9		-156.6	
Chi-Square	56.7		28.3		40.8	
Pseudo R^2	0.16		0.08		0.13	
Proportion of correct prediction	0.72		0.69		0.70	

Note: The numbers in parentheses are the ratios of the coefficients to their estimated asymptotic standard errors. N represents sample size, Log(L) denotes the maximum values of the log-likelihood function calculated, and Chi-square is a statistic for the null hypothesis that none of the explanatory variables except the intercept term affect the discrete choice decision.

[a] M.E. represents the average value of the marginal effect of the relevant variable for the probability of purchase intentions for Type II produce.

Table 4

Average Price Increments for Risk Reductions[a]
(in dollars)

Risk Reduction (percent)		Risk Reductions	Risk of Type I	Risk of Type II	Model (A)		Model (C)	
					Mean	S.D.[b]	Mean	S.D.[b]
RC1	33%	1/10000	<u>3/10000</u>	2/10000	0.80	0.16	0.76	0.15
RC2	83%	1/10000	6/50000	<u>1/50000</u>	0.80	0.16	0.76	0.15
RC3	10%	0.3/10000	<u>3/10000</u>	2.7/10000	0.80	0.17	0.74	0.16
RC4	10%	0.1/50000	1.1/50000	<u>1/50000</u>	0.80	0.17	0.74	0.17
RC5	50%	1.5/10000	<u>3/10000</u>	1.5/10000	0.80	0.15	0.76	0.14
RC6	50%	1/50000	2/50000	<u>1/50000</u>	0.80	0.17	0.74	0.17

[a] The price increments reported in this table were calculated for each consumer and were averaged over the sample.

[b] The standard deviation is equal to $\sqrt{\mathrm{var}(\hat{w})}$. Because the mean price increment, $\hat{w}$, is a function of the estimated coefficients of each probit model, $\hat{w} = f(\hat{\theta}) = f(\hat{\kappa},\hat{\beta},\hat{\lambda},\hat{\tau},\hat{c},\hat{d};Y,W,S)$ as defined in equation (10), the variance of $\hat{w}$ was approximated using a first-order Talyor series (Kmenta, page 486):

$$\mathrm{var}\,(\hat{w}) = \sum_i (\partial f/\partial\hat{\theta}_i)^2\, \mathrm{var}(\hat{\theta}_i) + 2 \sum_{i\neq j} (\partial f/\partial\hat{\theta}_i)(\partial f/\partial\hat{\theta}_j)\, \mathrm{cov}(\partial\hat{\theta}_i,\partial\hat{\theta}_j),$$

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Appendix A

Probit Estimates for the Discrete Choice Models with Sample Selection

Independent Variables	Model (B)		Model (C)	
	Discrete Choice Model[a]	Selection Model[a]	Discrete Choice Model	Selection Model
Intercept	0.933 (1.903)	1.411 (3.728)	0.640 (1.826)	1.443 (3.744)
Price Increase	-0.898 (-3.936)	-0.466 (-3.101)	-1.025 (-3.777)	-0.470 (-3.140)
Version	-0.530 (-2.774)		-0.683 (-2.851)	
Risk Reduction		0.0187 (2.449)		0.0200 (2.483)
Risk I		-0.0102 (-1.656)		-0.0135 (-2.033)
Risk Reduction* Serious-Commercial	0.0014 (2.055)		0.0048 (2.607)	
Income	-0.0005 (-0.189)		-0.0006 (-0.238)	
Education	-0.0383 (-1.326)			
Education* Risk-Redction			-0.0017 (-2.128)	
No. children	-0.0362 (-0.534)		0.0983 (0.636)	
Ask Doctor	0.0872 (0.645)		-0.0677 (-0.846)	
Age		-0.0068 (-1.293)		-0.0079 (-1.449)
Sex		-0.0740 (-0.574)		-0.111 (-0.828)
Serious-Organic		0.0419 (1.318)		0.0383 (1.152)
Serious-Commercial		-0.0471 (-1.320)		-0.0196 (-0.524)
Serious-Tested		-0.0995 (-2.707)		-0.113 (-3.002)
Rho (ρ)	0.91 (11.42)		0.79 (4.441)	
N	276	430	276	430
Log(L)	-421.3		-419.1	

Note: The numbers in paranthese are the ratios of the coefficients to their estimated asymptotic standard errors. N represents sample size and Log(L) denotes the maximum values of the log-likelihood functions calculated. Rho (ρ) designates a correlation coefficient of disturbances associated with the bivariate probit model.

[a] Discrete choice models estimate factors affecting contingent choices of Type II produce, and Selection models estimate factors affecting contingent choices (either Type I or Type II produce).

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