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THE EFFECT OF AMBIGUITY ON CONSUMERS' WILLINGNESS TO PAY FOR PESTICIDE-RESIDUE CERTIFICATION ON APPLES

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ABSTRACT

THE EFFECT OF AMBIGUITY ON CONSUMERS' WILLINGNESS TO PAY FOR PESTICIDE-RESIDUE CERTIFICATION ON APPLES

By

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Consumers often face ambiguity about the health risks posed by pesticide residues in the food they buy. Ambiguity is defined as uncertainty about the probability of an outcome. It results because of the inherent difficulty in assessing the levels and hazards of pesticide residues in food. Yet standard economic models of decision making that are commonly used to assess choices involving risk assume that consumers can assign numerical probabilities to outcomes with total certainty.

This research develops a conceptual framework of consumers' willingness to pay (WTP) for pesticide-residue certification on apples in the face of ambiguity about risks. It uses Segal's model of choice under ambiguity to show that the marginal value of a reduction in ambiguity is positive and that willingness to pay for pesticide-residue certification decreases with initial perceptions of ambiguity.

The study uses the results of a contingent-valuation survey of Michigan residents' apple-purchasing behavior and attitudes about the risks from pesticide residues

to test these findings. Heckman's model is used to estimate ~~the demand for certified~~ apples. The model asserts that the demand for certified apples is a two-stage process: the consumer first decides whether to buy certified or regular apples; he/she then decides how many apples to buy.

The probit results in the first stage indicate that ~~both~~ initial ambiguity and changes in ambiguity associated with switching from regular to certified apples are important factors compelling consumers to choose certified over regular apples. The empirical results show that consumers are willing to pay a 32% premium on each pound of apples that offers certification that the apples meet certain standards for pesticide residues. This amount varies with perceived ambiguity about risks, suggesting that consumers are interested in reducing not only the risks from pesticide residues but also the ambiguity about those risks.

The findings suggest that certifying that food meets certain standards for pesticide residues may have value by providing consumers with information about the current risks they face. The conceptual results suggest that ambiguity about risks should be incorporated into models of decision making under risk when the probabilities of outcomes are not "crisp."

To my parents

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CHAPTER 1: INTRODUCTION

Problem Statement

Consumers have become increasingly concerned about the potential health effects of pesticide residues in food (Food Marketing Institute 1990). Part of the concern stems from the fact that when making food choices, consumers often face **ambiguity** about the health risks posed by pesticide residues. Ambiguity is defined as uncertainty about the probability of an outcome.[1] It results because of the inherent difficulty in assessing the levels and hazards of pesticide residues in food. Since pesticide residues are undetectable in food and since food is generally not labeled for its residue levels, consumers do not know the exact levels of pesticide residues they ingest. Furthermore, consumers receive conflicting information about the potential health effects of pesticide residues, and they may not trust that policies regarding allowable levels of residues are adequate or are being strictly enforced (van Ravenswaay 1992).

To design policies that effectively address consumers' concerns, policy makers should understand how consumers make choices in the face of potential risks from pesticide residues. However, standard economic models of consumer choice under risk that are commonly used to assess such choices (e.g., Jones-Lee 1974) assume that decision makers are able to accurately assess the probabilities of the potential outcomes associated with a choice (i.e. perceptions about risks are "crisp" and people can assign numerical probabilities to outcomes with total certainty). These models predict that

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[1] In this research, ambiguity refers to only the uncertainty about the probability of an outcome; it assumes there is no uncertainty about the types of potential outcomes.

consumers' willingness to pay for a reduction in risk increases with both the initial, or "baseline," risk and the magnitude of the risk reduction.

Contrary to these theoretical predictions, however, van Ravenswaay and Hoehn (1991) found empirically that in the case of pesticide residues in food, perceptions of both initial risks and risk reductions explained very little of the variation in the willingness to pay for risk reduction. They used the results of a contingent valuation survey to estimate consumers' willingness to pay for apples that had been tested and certified to meet certain standards of pesticide residues. While risk perceptions were statistically significant in explaining apple purchases, people who perceived large initial risks from pesticide residues were willing to pay about the same amount for apples certified for pesticide residue levels as people who perceived small initial risks.

These findings motivated the present research which investigates whether consumers' willingness to pay for pesticide-residue certification is affected by the uncertainty or "ambiguity" they perceive about the risks they face. The study uses the case of pesticide residues in apples to explore the hypothesis that ambiguity about risks is an important determinant of consumers' willingness to pay for residue certification.

Segal's (1987) model of choice which incorporates ambiguity into a generalized expected utility model is used to develop hypotheses about (1) consumers' WTP for residue certification, (2) the effect of perceived initial or baseline risk and ambiguity on willingness to pay for certification, and (3) the effect of the perceived reductions in risk and ambiguity associated with certification on WTP for certification.

These hypotheses were tested using the results of a contingent valuation telephone survey conducted in Michigan in June/July 1992. The survey asked Michigan residents about their apple-purchasing behavior in both actual and hypothetical situations. It also solicited their perceptions of the current risks from pesticide residues in food and their "sureness" about those risks. As is explained in chapter 4, these measures of "sureness" serve as proxies for a measure of ambiguity.

The survey considered two hypothetical food-labeling policies that potentially change consumers' perception of the risks posed by pesticide residues in apples. One policy permits certification and labeling of apples that have been produced without pesticides. The other policy permits certification and labeling of apples that meet federal standards for pesticide residues. Survey respondents were presented with a hypothetical shopping scenario and were asked to predict their apple-purchasing behavior. Respondents were then asked how their apple purchases and risk perceptions would change if they could choose between regular apples and apples that had been tested and certified to meet one of these standards for pesticide residues.

The data from the survey were used to evaluate the factors affecting the decision to buy certified apples and the demand for certified apples. The parameters from the demand equations were used to estimate consumers' willingness to pay for certification, the effects of baseline risk and ambiguity on willingness to pay for certification, and the effects of reductions in risks and ambiguity on WTP for certification.

If ambiguity about risks is an important determinant of consumers' WTP for certification, polices to reduce ambiguity may have value. Consumers may value knowing the standards for pesticide residues in food, for example, and what those standards mean. Similarly, information about what is being done to enforce the standards may be beneficial to consumers. This information helps consumers better assess the risks they face from pesticide residues without necessarily changing the actual risk that consumers face. Furthermore, a better understanding of the role of ambiguity in consumer choice may give us insight as to why consumers are willing to pay for certified apples when initial risks (i.e., the perceived risk associated with the regular apple) and risk reductions are perceived to be small. It may also have implications for the interpretation of existing estimates of WTP for reduced mortality and morbidity which assume no ambiguity.

Objectives

The objectives of this research can be summarized as follows:

1. Develop a conceptual framework of willingness to pay for pesticide-residue certification that incorporates perceptions about both risk and ambiguity about risks. This is done using Segal's model of choice, which incorporates ambiguity into the Rank-Dependent Expected Utility (RDEU) model;

2. Use the conceptual framework to develop hypotheses about the effect of "baseline" or "initial" risk and ambiguity on the willingness to pay for certification, and the effect of risk and ambiguity reduction on willingness to pay for certification;

3. Empirically test the hypotheses using the results of a contingent valuation survey that asks respondents about their apple purchasing behavior and about their risk and ambiguity perceptions.

The rest of this chapter illustrates the importance of ambiguity and presents some concepts and definitions of terms that will be used throughout the thesis. The chapter concludes with a presentation of the organization of the rest of the dissertation.

Illustration of Ambiguity

Ellsberg (1961) illustrates a situation of ambiguity using the following example. Suppose you have agreed to participate in an experiment in which one ball will be chosen from one of two urns, both containing 100 balls. In urn I there are 100 balls, but you do not know the proportion of red and black balls. In urn II there are 50 red and 50 black balls. You indicate which color you prefer to bet on (red or black) and which urn you want the ball to be drawn from. If a ball of your color is chosen, you win $100, otherwise you receive nothing. If you are like most of the subjects in Ellsberg's original experiment, you will be indifferent between betting on a red ball or betting on a black ball, but once the color is chosen (be it red or black) you would prefer to have a ball drawn from urn II (the unambiguous urn) than from urn I (the ambiguous urn). However, if all distributions of red and black balls are equally likely in the ambiguous urn,[2] the expected probability of drawing either color ball is 0.5. Since the probability of drawing a red or black ball in the unambiguous ball is also 0.5, you should be indifferent between the urns. That you are not indifferent about the urns suggests that the uncertainty about the probability of drawing a particular ball in the ambiguous urn may affect your choice of urn.

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[2] All distributions would be equally likely if you used the "Principle of Insufficient Reason" which states that "if there is no evidence leading one to believe that one event from an exhaustive set of mutually exclusive events is more likely to occur than another, then the events should be judged equally probable" (Luce and Raiffa 1988, 48).

Definitions of Terms

This section establishes the terminology used throughout the rest the dissertation when discussing consumer choice under uncertainty.

In this research, the term "uncertainty" refers to a situation in which one does not know for certain what the outcome or consequence of an action will be. In Savage's (1954) framework for decision making under uncertainty, the decision maker chooses between "acts" (also called "lotteries" or "alternatives").[3] These are probabilistic choices available to the decision maker. Nature is said to choose among "states of the world" (also called "states of nature" or "states"). Each act/state combination yields an "outcome" or "consequence" from which the decision maker derives utility. When making a choice, the decision maker does not know which state of the world nature will choose, and thus chooses an act under uncertainty. The decision maker assesses the probability of each possible state of the world (and thus the probability of each outcome). Each act, then, has associated with it a probability distribution over outcomes. The outcome is thus a random variable with a probability distribution.[4]

The states of nature are usually assumed to "form a mutually exclusive and exhaustive listing of those aspects of nature which are relevant to this particular choice problem" (Luce and Raiffa 1988). The states of the world are considered independent

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[3] The terms "act," "action," and "lottery" are used interchangeably throughout the text.

[4] For a given "act," the probability distribution over "states" is identical to the probability distribution over "outcomes." One can therefore talk about the probability distribution over either without a change in meaning.

of the act chosen. The probabilities of the states of the world "rain" and "no rain," for example, are independent of the acts "carry an umbrella" and "do not carry an umbrella." If the probabilities of the states depend on the act chosen one may alternatively assign to states "conditional" probabilities (Jeffrey 1983) which depend upon which act is chosen.

This study presented respondents with a hypothetical market in which there were available both regular apples (the kind they usually buy) and apples that had been tested and certified by the federal government to meet federal standards for pesticide residues (or, for half the sample, to have been grown without pesticides). Respondents were asked to indicate whether they would select the regular apples, the tested apples, some of both, or none at all. The choice of apple type is considered an act. The states of nature are (1) "experience an adverse health outcome someday because of pesticide residues in apples" and (2) "do not experience an adverse health outcome someday because of pesticide residues in apples."[5] The probabilities of the states of nature are "conditional" upon which type of apple is chosen. The outcome depends on which type of apple was chosen, as well as which state of nature prevails. The choice scenario for apples is depicted diagrammatically in Table 1-1.

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[5] The state of nature could alternatively be characterized as (1) pesticide residues are safe and (2) pesticide residues are not safe. This depiction of the states conforms to the Savage (1954) framework in which the probabilities of the states are immutable and do not depend on the act chosen. With this representation, however, one cannot take actions (buying certified apples, for example) to reduce the risks from pesticide residues. To develop a framework for the WTP for certification that depends on the probability of experiencing an adverse health outcome someday because of pesticide residues, this research uses "conditional" probabilities that depend on which type of apple one chooses.

Table 1-1: Acts, States, and Outcomes in the Pesticide Residue Case Study

	State	
	s_1: experience an adverse health outcome someday because of pesticide residues in apples	s_2: experience an adverse health outcome someday because of pesticide residues in apples
Act	**Outcome**	
X_1: buy only regular apples	$P(s_1)$ under $X_1 = \pi^1$	$P(s_2)$ under $X_1 = 1-\pi^1$
	x_1^1: consume reg apples, suffer adverse health outcome	x_2^1: consume reg apples, do not suffer adverse health outcome
X_2: buy only tested apples	$P(s_1)$ under $X_2 = \pi^2$	$P(s_2)$ under $X_2 = 1-\pi^2$
	x_1^2 : consume tested apples, suffer adverse health outcome	x_2^2: consume tested apples, do not suffer adverse health outcome
X_3: buy some of both types of apples	$P(s_1)$ under $X_3 = \pi^3$	$P(s_2)$ under $X_3 = 1-\pi^3$
	x_1^3: consume both types of apples, suffer adverse health outcome	x_2^3: consume both types of apples, do not suffer adverse health outcome
X_4: do not buy apples	$P(s_1)$ under $X_4 = \pi^4$	$P(s_2)$ under $X_4 = 1-\pi^4$
	x_1^4: do not consume apples, suffer adverse health outcome	x_2^4: do not consume any apples, do not suffer adverse health outcome

Notes

x_s^X = outcome resulting from act X and state s.

Most of the literature on risk discusses choices between "acts" such as those presented in Table 1-1 as choices among "lotteries;" that convention will be used here. The following notation will be used to represent such lotteries: $X_i=(x_1^i,\pi_1^i; x_2^i,\pi_2^i;...x_n^i,\pi_n^i)$ is a one-stage lottery (or act) called X_i that offers the prize x_1^i, with probability π_1^i, x_2^i with probability π_2^i, up to x_n^i with probability π_n^i.[6] The text later uses a two-stage lottery to introduce ambiguity into the decision calculus. A two-stage lottery is a lottery in which the prizes are tickets to another lottery; it is represented by $A=(X_1,q^1; X_2,q^2;...X_m,q^m)$. The symbol "$\pi$" is used to denote the probabilities in one-stage lotteries; "q" is used in two-stage lotteries to denote the probabilities of winning tickets to a one-stage lottery. Capital letters are used to denote lotteries; lower-case letters are used to denote prizes or final consumption goods.

"Risk," "ambiguity," and "ignorance" fall under the general rubric of "uncertainty" and are distinguished by the degree to which one can accurately specify the probability distribution over states (Einhorn and Hogarth 1985).

"Risk" refers to uncertainty about which outcome (or state) will prevail. There is no uncertainty about the probabilities of outcomes (or states). Decisions under risk can be described by one-stage lotteries. If one knows with certainty the probability that pesticide residues in apples cause adverse health outcomes, the example in Table 1-1 is considered a decision under "risk."

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[6] If there are only two possible outcomes to a lottery the subscript denoting the outcome is often dropped; the superscript denoting the lottery number is dropped when the discussion concerns only one lottery or a general set of lotteries.

"Ignorance" refers to a situation in which one has no knowledge about the probability distribution over states.

"Ambiguity" refers to uncertainty about the probabilities of outcomes (or states). When there is ambiguity, the probability of each state is itself a random variable. Each point on the probability distribution over states then has its own probability distribution over probabilities (called "second-order probability distribution," or SOP) (Marschak 1975). For example, food-consumption choices when pesticide residues may be present are made under ambiguity when one does not know whether an adverse health effect will result **and** one cannot assign probabilities to health states with certainty. Ambiguity can alternatively be described as a continuum, with risk at one extreme and ignorance at the other. A case of zero ambiguity would be considered "risk"; complete ambiguity would be considered "ignorance."

The definitions of "uncertainty," "risk," "ambiguity," and "ignorance" (adapted from Einhorn and Hogarth 1985) are shown schematically in Figure 1-1.

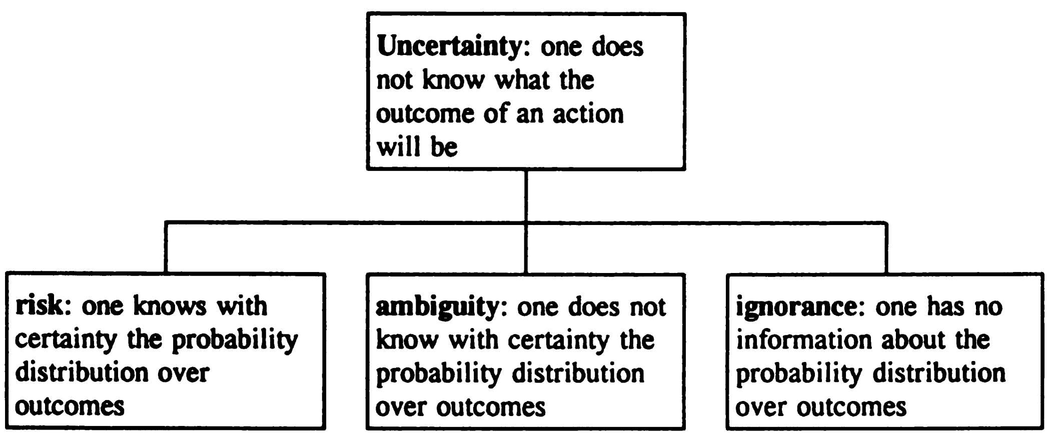

Figure 1-1: Definitions of uncertainty, risk, ambiguity, and ignorance

Figure 1-2 below shows a continuous first-order probability distribution (FOP - represented by f(x)) over outcomes, x (or over states) when there is no ambiguity about the probability of each state of the world. Each point on this distribution is a point estimate of the probability of a particular state (objectively or subjectively determined). In Figure 1-3 each point on the FOP distribution in Figure 1-2 has its own second-order probability (SOP) distribution (represented by g[f(x)]). The amount of ambiguity is the spread, or variance, of the SOP distribution. The next chapter shows how the spread of the SOP distributions of Figure 1-3 can be accounted for in a model of choice under uncertainty.

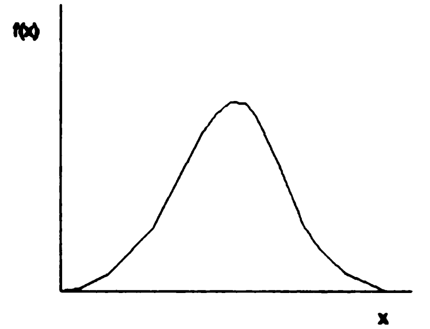

Figure 1-2: FOP probability distribution over outcomes, x (or states) when there is no ambiguity

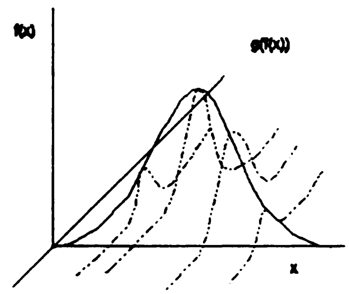

Figure 1-3: SOP probability distribution over outcome, x (or states) when the probability of each outcome is ambiguous

The concept of the probability of an outcome is itself subject to interpretation. There are two main types of probability:

1) **Objectivistic (or frequency)**: The probability of a given outcome is considered a property of that outcome. This property can be determined by repeated experimentation. The probability is the proportion of the experiments that result in the outcome. The probability of a coin toss landing heads, for example, may be determined objectively by performing an experiment in which the coin is tossed numerous times. One may then objectively estimate the probability of heads as 0.5.

2) **Subjectivistic (or personal)**: This view holds that probability is a subjective set of beliefs about risk which may or may not be based on a frequency interpretation of probability. Two individuals faced with the same evidence may state divergent probabilities, both of which may be reasonable. One individual may hold the subjective view that the probability of rain tomorrow is 0.9, while another may estimate the probability as 0.7; both probabilities are reasonable.

Our research maintains that people have subjective views about the objective probability (or frequency) of an outcome. People also have a certain degree of confidence in their estimate. If, for example, someone saw a coin tossed twice and it landed heads once and tails once, he/she would estimate that the probability of that coin landing heads was 0.5. Similarly, if he/she saw the coin tossed 1000 times and the result was 500 heads and 500 tails, he/she would again assign 0.5 probability that the flip of the coin would result in heads. However, he/she would have more "confidence" in the second estimate than in the first and his/her SOP distribution would have a smaller variance.

Organization of Dissertation

The rest of the dissertation is organized as follows. chapter 2 reviews the subjective expected utility (SEU) model, the assumptions and postulates undergirding it, and the failure of the model to account for ambiguity. It then presents several models of choice that incorporate ambiguity. The purpose of the literature review is to highlight the importance of ambiguity in decision making and to evaluate the various models that incorporate ambiguity in order to select the best model. Chapter 3 presents the conceptual framework used in this study to derive the hypotheses about consumers' willingness to pay for residue certification, the effect of baseline risk and ambiguity on WTP for certification, and the effect of reductions in risk and ambiguity on WTP for certification. It also discusses how demand analysis can be used to test the hypotheses. Chapter 4 discusses the survey used to measure consumers' apple purchasing behavior and the measures of risk and ambiguity used. Chapter 5 presents some descriptive statistics of the survey results. It then discusses the empirical model used to test the hypotheses and an presents an analysis of the results. The summary and policy implications are presented in chapter 6.

CHAPTER 2: LITERATURE REVIEW

The expected utility (EU) model as axiomatized by von Neumann and Morgenstern (1947) and the subjective expected utility model (SEU) as axiomatized by Savage (1954) are normative models of decision making under risk. The expected utility model asserts that if a decision maker conforms to a set of axioms that govern "rational" behavior, then his/her choices among alternative acts can be ranked according to their expected utility. The decision maker should choose the act that results in the highest expected utility, where the weights attached to utility in various states of the world are the objective probabilities of those states. In the SEU model, decision makers do not use "objective" probabilities to weight the utilities, but rather use subjective beliefs about the likelihood of various states.[7]

This chapter first reviews the SEU model and the postulates that undergird it. It then demonstrates how the model fails when probabilities are ambiguous. The chapter reviews several models of choice that explicitly accommodate ambiguity. These models can be divided into three types: (1) intuitive models that offer non-axiomatized alternatives to expected utility, (2) data-based models that weight the expected probability of an outcome to account for ambiguity, and (3) theoretical models that weight the entire second-order probability distribution (SOP) over outcomes non-linearly by relaxing one or more of the axioms of SEU (usually the "sure-thing" principle, or the independence axiom in EU).

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[7] The rest of the discussion in this section uses the subjective expected utility (SEU) model when demonstrating the importance of ambiguity. However, most of the discussion applies to the expected utility model as well.

The purpose of this chapter is to demonstrate the importance of ambiguity in decision making under uncertainty and to select a theoretically sound model of choice that accommodates ambiguity. Segal's model of decision making under ambiguity is described at the end of the chapter; this model is used in chapter 3 to develop hypotheses about consumers' willingness to pay (WTP) for pesticide-residue certification on apples and the effect of risk and ambiguity on WTP.

Models of Choice

Model of Choice Under Risk

The Subjective Expected Utility Model

The subjective expected utility model offers a normative framework of how people should rank "acts" in an uncertain world. Subjective expected utility for a given act is the weighted average of the utility of the possible outcomes (or consequences) associated with that act in different states of the world, where the weights are the subjective probabilities of the various states occurring. Given an individual's preferences over consequences, the individual should choose the act that has the highest expected utility.[8]

Consider the simple example of a decision maker deciding between two acts (X_1, X_2). Nature will choose one of three possible states (s_1, s_2, or s_3). Each act/state

[8] Hirschleifer and Riley (1992) make the "crucial distinction" between the utility of consequences and the utility of actions. Utility attaches directly to consequences but only derivatively to actions. This study maintains this distinction and follows their notation of u(x) to represent a person's preference-scaling function (or elementary-utility function) over the consequences, x; U(X) will be used to represent the person's derived preference ordering over acts, X.

combination yields an outcome: (x_1^1, x_2^1, x_3^1) are the consequences associated with act X_1 under states 1, 2, and 3; (x_1^2, x_2^2, x_3^2) are the consequences associated with act X_2 under states 1, 2, and 3. The decision maker's subjective beliefs about the unconditional likelihood of states s_1, s_2, and s_3 are represented by π_1, π_2, and π_3. The decision maker calculates the following:

$$SEU(X_1) = \pi_1 u(x_1^1) + \pi_2 u(x_2^1) + \pi_3 u(x_3^1)$$

$$SEU(X_2) = \pi_1 u(x_1^2) + \pi_2 u(x_2^2) + \pi_3 u(x_3^2)$$

He/she then chooses the act with the highest subjective expected utility.

When the states of nature are continuous between 1 and n, the outcomes associated with act i are continuous between x_1^i and x_n^i. The individual then chooses the highest among:

$$SEU(X_1) = \int_{s=1}^{n} \pi_s u(x_s^1) dx \tag{2-1}$$

$$SEU(X_2) = \int_{s=1}^{n} \pi_s u(x_s^2) dx \tag{2-2}$$

Assumptions of the SEU Model

The SEU model is valid only under certain assumptions about the decision maker's behavior. The model requires that decision makers adhere to certain axioms or postulates of behavior that lead to these behavioral assumptions. This section reviews those assumptions and postulates. The section following demonstrates situations in which it may be inappropriate to apply them to our decision maker.

The assumptions of the subjective expected utility model are listed as A1 through A4 below (adapted from Gärdenfors and Sahlin 1988).

A1: The values of the outcomes in a decision situation are determined by a utility measure which assigns numerical values to the outcomes.

A2: When determining the value of a decision alternative the only information about the decision maker's wants and desires that is exploited is the utilities of the possible outcomes of the alternatives, i.e., factors other than the utilities of the outcomes - such as risk involved - do **not** influence the value of the alternative.

A3: A decision maker's beliefs about the states of the world in a given situation can be represented by a unique probability measure defined over states. For each state s the decision maker thus assigns a probability value P(s) so that the sum of all these values taken over the set S is 1. These probabilities are subjective.

A4: For all states and all alternatives, the probability of the state is independent of the act chosen.

The foundations for these assumptions are Savage's (1954) axioms or rationality postulates P1 through P4 below (adapted from Ellsberg 1961).

Postulates of the SEU Model

P1. There is a complete ordering of gambles or "actions" (either Act 1 is preferred to Act 2, Act 2 is preferred to Act 1, or one is indifferent between Act 1 and Act 2).

P2. The choice between two actions must be unaffected by the value of payoffs corresponding to states for which both actions have the same payoff. (Sure Thing Principle)

P3. Knowledge of an event[9] cannot establish a new preference among consequences or reverse an old one, and no preference among consequences can be reduced to indifference by knowledge of an event.[10]

P4. The choice of which state a person prefers to stake a prize should not be affected by the size of the prize.

These axioms justify the use of the SEU model as a framework for decision making under uncertainty. Further, A3 justifies reducing all decisions under uncertainty to decisions under risk. The subjective expected utility model assumes decision makers' beliefs about the likelihood of states of the world can be represented by a single probability estimate. Savage himself was aware of the problem "ambiguity" might pose to the SEU model as demonstrated in the following passage:

> ...there seem to be some probability relations about which we feel relatively "sure" as compared with others. When our opinions, as reflected in real or envisaged action, are inconsistent, we sacrifice the unsure opinions to the sure ones. The notion of "sure" and "unsure" introduced here is vague, and my complaint is precisely that neither the theory of personal probability, as it is developed in this book, nor any other device known to me renders the notion less vague (Savage 1954, 57-58).

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[9] An event is a set of states. An event can also be a set of one state, in which case a state and an event are the same thing.

[10] This postulate simply helps define what is an "act" and what is a "consequence." The example given by Savage (1954, 25) is that of a person going on a picnic that will be held at either the beach or near tennis courts. If the "consequences" are the possession of a tennis racket or the possession of a bathing suit, clearly the preference over "consequences" would depend on where the picnic were held. P3 stipulates that the "consequences" should instead be defined as "enjoy a swim," or "enjoy a game of tennis," etc.

Failure of the SEU Model in the Presence of Ambiguity

Ellsberg (1961) demonstrates that in situations of high ambiguity, people do not conform to the Savage postulates (P1 and P2 in particular); the subjective expected utility model is then invalidated. Ellsberg (1961) defines ambiguity as the degree of confidence one has in his/her estimate of relative likelihoods of outcomes.

Ellsberg's (1961) urn example described in chapter 1 demonstrates a situation in which the Savage postulates are violated. Reconsider the two urns: In urn I, there are 100 red and black balls in a proportion unknown to you. In urn II there are exactly 50 red balls and 50 black balls. Ellsberg then asks the following questions:

1. "Which do you prefer to bet on , Red_I or $Black_I$: or are you indifferent?" That is, drawing a ball from Urn I, on which "event" do you prefer the \$100 stake, red or black: or do you care?
2. "Which would you prefer to bet on, Red_{II} or $Black_{II}$?"
3. "Which do you prefer to bet on, Red_I or Red_{II}?"
4. "Which do you prefer to bet on, $Black_I$ or $Black_{II}$?"

If you are like most people, you will be indifferent in both the first and the second case. Yet once the color is determined (be it red or black) you would prefer to bet on the unambiguous urn (urn II).[11] This pattern of choice violates Savage's first postulate that there is a complete ordering of gambles or "actions" and it demonstrates

[11] This example falls under the "economics of uncertainty," where one must make a terminal decision, rather than under the "economics of information" in which the decision maker has the option of paying to acquire more information. For more on this distinction, see Hirschleifer and Riley (1992).

that personal probabilities cannot always be determined by observing choices among gambles (as is implied by Ramsey (1931) and Savage (1954)).

If you prefer to bet on Red_{II} rather than Red_I (i.e., you are not indifferent), assumption A3 above leads us to conclude that you must view Red_{II} as more likely than Red_I (i.e., $P(Red_{II}) > P(Red_I)$).[12] Similarly, if you prefer to bet on $Black_{II}$ over $Black_I$ this should reflect your belief that $Black_{II}$ is more probable than $Black_I$ (i.e., $P(Black_{II}) > P(Black_I)$). But if the latter holds then it must also be true that $P(\text{not } Red_{II}) > P(\text{not } Red_I)$, which is a contradiction to the former. It is thus impossible to infer meaningful, unique probabilities from your choices and you are violating Savage's first postulate since there is no clear ordering over preferences. The justification for using the subjective expected utility framework is thus in doubt.

Ellsberg (1961) also presents an example that shows how the sure-thing axiom (P2 above) is violated. Suppose you are presented with two choice pairs. In the first choice pair, there is an urn filled with 30 red balls and 60 yellow and black balls in a proportion unknown to you. One ball will be chosen from the urn. You may bet that the chosen ball will be red or you may bet that it will black. The prize will be $100 for a correct prediction. The payoffs corresponding to each choice are presented in Table 2-1. Would you prefer to bet on red (choice I) or on black (choice II)?

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[12] A3 suggests that one can always assign a unique probability to a state of the world. One can thus always compare the probability of one state to the probability of another.

Table 2-1: Ellsberg's Urn - First Choice Pair

Choice	Payoff		
	Red (N=30)	Black ($0 \leq N \leq 60$)	Yellow ($0 \leq N \leq 60$)
I. Bet on Red	$100	$0	$0
II. Bet on Black	$0	$100	$0

N = Number of balls

In the second choice pair, you must choose between betting on (red or yellow) and betting on (red or black). This choice and its payoffs are depicted in Table 2-2.

Table 2-2: Ellsberg's Urn - Second Choice Pair

Choice	Payoff		
	Red (N=30)	Black ($0 \leq N \leq 60$)	Yellow ($0 \leq N \leq 60$)
III. Bet on (Red or Yellow)	$100	$0	$100
IV. Bet on (Black or Yellow)	$0	$100	$100

N = Number of balls

Most people prefer Choice I to Choice II, but prefer Choice IV to Choice III. This pattern of choice violates the Sure-Thing Principle (P2 above). In the first choice scenario, the payoff is the same for both actions if a yellow ball is drawn (payoff of $0). The Sure-Thing Principle says that this payoff should therefore be ignored.[13]

[13] Savage (1954, 21) gives the following example to demonstrate the "sure-thing principle:" "A businessman contemplates buying a certain piece of property. He considers the outcome of the next presidential election relevant to the attractiveness of the purchase. So, to clarify the matter for himself, he asks whether he would buy if he knew that the Republican candidate were going to win, and decides that he would do so. Similarly, he considers whether he would buy if he knew that the Democratic candidate were going to win, and again finds that he would do so. Seeing that he would buy in

Similarly in the second choice scenario, the payoff for yellow is the same for both actions ($100 if yellow is drawn). This payoff should also be ignored. Ignoring the payoff under yellow, the payoffs of the two choice situations are identical. According to the Sure-Thing Principle, if you prefer choice I, you should also prefer choice III.

The Sure-Thing Principle and the Independence Axiom

The sure-thing principle can also be stated as follows: "Suppose that we are considering two actions A (bet on red) and B (bet on black) and that these will have the same outcome ($0 payoff) if E (yellow ball drawn) occurs, but will yield different outcomes when E does not occur. Suppose that A is preferred to B. Now consider two acts A′ (bet on [red or yellow]) and B′ (bet on [black or yellow]) such that

- A′ yields the same outcome as A provided E does not occur
- B′ yields the same outcome as B provided E does not occur
- A′ and B′ yield the same outcome whenever E occurs.

Savage argues that if A is preferred to B, we should also prefer A′ to B′ (Quiggin 1993, 9). When choosing between acts, we should ignore states in which acts yield the same outcome.

The sure thing principle is analogous to the independence axiom in EU which states that if for acts X and Y, $X \succeq Y$, then for any number $r \in [0,1]$ and any act Z, $rX+(1-r)Z \succeq rY+(1-r)Z$. Preferences between two lotteries should be independent of any common components.

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either event, he decides that he should buy, even though he does not know which event obtains."

The independence axiom (sure-thing principle) is the cornerstone of the Expected Utility (Subjective Expected Utility) theory. This axiom restricts the preference functional to be "linear in the probabilities." That is, it must be representable as the mathematical expectation of some von Neumann-Morgenstern utility index defined over the set of pure outcomes" (Machina 1988, 216).

However, as just shown, the independence axiom is commonly violated in situations of ambiguity. Without the independence axiom, the preference functional is not restricted to being linear in the probabilities. Several of the models that have been developed to accommodate situations of ambiguity are not linear in the probabilities. The next section reviews several of these models as well as other models of choice under ambiguity.

Models of Choice Under Ambiguity

There has been a plethora of empirical studies over the last twenty five years demonstrating that people prefer a choice situation in which they have more information regarding the probabilities of states to one in which little is known about the probabilities of states, even if the mean probability of states in the two choices is the same.[14] In other words, people prefer situations of low ambiguity to situations of high ambiguity. Yet in their traditional form, the EU and SEU cannot accommodate ambiguity because probabilities about probabilities are averaged out. Instead, both EU

[14] See Camerer and Weber (1992) for a review of several empirical studies of ambiguity.

and SEU use point estimates of probabilities even though the decision maker may not know the probability distribution over states with certainty.

Ever since Ellsberg's (1961) seminal paper, several researchers have tried to incorporate ambiguity into models of decision making under risk. There have been three types of models: 1) non-axiomatic intuitive models, 2) models based on data generated by laboratory experiments, and 3) theoretical models that weight the second-order probability distribution non linearly. This section reviews some of the approaches taken in each category of model.

Intuitive Models

State-Dependent Utility Approach

Expected utility theory assumes that the utility derived from a consequence is independent of the state in which the consequence occurs. State-dependent utility theory, on the other hand, allows utility to depend on the state in which the consequence occurs. Although this approach violates A2 above, it has been used to account for the effect of ambiguity on decision making. Smith (1969) proves that in the Ellsberg (1961) urn example, preferences are consistent when the probabilities are the same for the two urns, provided that the utilities of payoffs in the two urns are different. He says "the utility of money or other rewards is not independent of the circumstances under which it is obtained. The utilities in the payoff matrix may have arguments other than what appears to be the 'objective' reward" (Smith 1969, 325). In other words, ambiguity about the probability of states may influence the utility of the consequences obtained in the states.

Consider the case of apple consumption. An apple eater may derive utility from not only the quantity of apples consumed, but also from knowing that the pesticide residues on those apples will not cause adverse health effects someday. The probability of such an occurrence as well as the ambiguity about that probability may be direct arguments in the utility function.

Winkler (1991) also argues that the effects of ambiguity operate through the decision maker's preferences rather than through the probabilities. Ambiguity may increase the feelings of "regret" or "blame" if a poor outcome results (such as adverse health effects from pesticide residues), and satisfaction or joy if a good outcome results. This justifies an expanded consequence space that may include attributes (such as risk or ambiguity) other than the monetary payoff received.

Sarin and Winkler (1992) propose a model that permits a decision maker's preferences to depend on the ambiguity about the probability of an event. Consider a simple lottery X, that yields a monetary payoff x_1 in state 1 and x_2 in state 2. Assume that $x_1 > x_2$, the assessed probability of state 1 is π, and the assessed probability of state 2 is $1-\pi$. The expected utility of this lottery is then:

$$U(X) = \pi u(x_1) + (1-\pi) u(x_2) \tag{2-3}$$

where u represents the decision maker's von Neumann-Morgenstern utility function.

If π is ambiguous then the utilities are replaced by modified utilities, V: $V[u(x_1)|u(x_2)]$ and $V[u(x_2)|u(x_1)]$.[15] The modified utility depends of the degree of

[15] The capital letter V represents the value function when the value of the lottery is not represented by its expected utility.

ambiguity present in the probabilities of each state. As x_1 approaches x_2, $V[u(x_1)|u(x_2)]$ approaches $u(x_1)$ and $V[u(x_2)|u(x_1)]$ approaches $u(x_2)$. Although the modified utilities could be appropriate in non-ambiguous situations as well, the authors argue that the sense of elation or regret "would seem to be heightened and especially salient when ambiguity is present" (Sarin and Winkler 1992, 394).

The general approach of accounting for the effects of ambiguity by expanding the consequence space of utilities is similar to "regret theory" developed by Loomes and Sudgen (1982). Regret theory compares what is received with what could have been received if a different action had been taken but the same state of the world obtained. Sarin and Winkler compare what is received with what could have been received if the same action was chosen but a different state of the world obtained.

State-dependent utilities are not unique to situations of ambiguity. Non-ambiguous risk can also lead to feelings of regret or the assignment of credit or blame. This approach is thus appropriate for situations of both risk and ambiguity.

Camerer and Weber (1992) argue that the choice of whether to model decision making under ambiguity by adjusting the probabilities or by altering the preferences is a matter of taste. "The choice between the two approaches turns crucially on whether one believes likelihood estimates and decision weights must be equal. Those who advocate modifying utilities are reluctant to let likelihood and decision weights differ (e.g., Winkler 1991). Those who are willing to allow a difference may find utility modification cumbersome or tautological" (Camerer and Weber 1992, 343).

Degree of Confidence in Risk Estimate

Ellsberg (1961), Gärdenfors and Sahlin (1982, 1983), and Levi (1974, 1982) present models of choice that account for ambiguity by assigning estimates of "confidence" to probability distributions over outcomes. Ellsberg (1961) demonstrates with his urn examples described above that there are some situations in which people do not act according to the Savage axioms and the justification for using expected utility framework disintegrates. Ellsberg (1961) does not suggest abandoning the Savage Axioms; he only suggests that there are some situations to which they do not apply. His thesis is that one must account for the "ambiguity of information" which is "a quality depending on the amount, type, reliability and 'unanimity' of information, and giving rise to one's degree of 'confidence' in an estimate of relative likelihoods" (Ellsberg 1961, 657). Although Ellsberg (1961) does not make the explicit analogy himself, higher confidence corresponds to a tighter SOP.[16] According to Ellsberg (1961), the level of confidence in a probability distribution over outcomes is a function of the "ambiguity of information." This research is concerned primarily with the level of ambiguity rather than with the sources of ambiguity. It thus concentrates on Ellsberg's (1961) "confidence" and not on the "ambiguity of information."

Ellsberg's (1961) model of choice accommodates ambiguity by including a measure of the degree of confidence in the probability distribution over states as a

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[16] To be consistent with the distinction between "risk," "ambiguity," and "ignorance" made in Chapter 1, if ambiguity is to be measured by the degree of confidence one has in the probability estimate of a state, it would have to exclude the endpoints. That is, "total confidence" would be a situation of risk, and "total lack of confidence" would be a situation of ignorance.

parameter in the choice model. Let ρ $(0<\rho<1)$ be the decision maker's degree of confidence in his/her estimated probability distribution over states of nature, y_o. The distribution y_o is an "estimated" probability distribution, obtained by "compounding various probability judgments of varying degree of reliability ... to eliminate certain probability distributions over the states of nature as 'unreasonable,' and assign weights to others" (Ellsberg 1961, 661). This estimated probability distribution "reflects all of [the decision maker's] judgments on the relative likelihood of distributions, including judgments of equal likelihood" (Ellsberg 1961, 664).

The decision maker divides the world into several states, only one of which will actually result. He/she assesses the probability of the occurrence of each state of the world; the probabilities of all the states of the world must sum to one. Associated with each state of the world for a given act X is an outcome. Est_X is the expected value of the possible outcomes associated with act X and probability distribution y_o. Min_X is the expected value of the possible outcomes associated with act X and the worst possible probability distribution over outcomes. The decision process Ellsberg (1961) presents for choosing among acts is the following:[17]

1) For each act X, calculate the value of the index:

$$\rho \cdot est_X + (1-\rho) \cdot min_X$$

2) Choose the act that yields the highest index.

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[17] Ellsberg converts all the outcomes (min_x and est_x) into utility terms before calculating the index.

The decision maker's reasoning behind using this decision rule in deciding between two actions, I and II, might be as follows: "In terms of my best estimates of probabilities, action I has almost as high an expectation as action II. But if my best guesses should be rotten, which wouldn't surprise me, action I gives me better protection; the worst expectation that looks reasonably possible isn't much worse than the 'best guess' expectation, whereas with action II it looks possible that my expectation could be really terrible" (Ellsberg 1961, 662).

The "ambiguity of information approach" implies that mistrust of information, sources of information, or one's ability to effectively use information can affect choice decisions between two outcomes that otherwise have the same expected value. As Ellsberg says, "'Ambiguity' may be high (and the confidence in any particular estimate of probabilities low) even where there is ample quantity of information, when there are questions of reliability and relevance of information, and particularly where there is conflicting opinion and evidence" (Ellsberg 1961, 659).

Consider the apple choice problem of the present research cast in Ellsberg's (1961) framework. As in Table 1-1, there are 4 acts from which a survey respondent may choose: 1) consume regular apples only, 2) consume tested apples only, 3) consume some of both, or 4) consume none at all. There are two relevant states of the world: 1) experience an adverse health outcome someday because of pesticide residues in apples, and 2) do not experience an adverse health effect from pesticide residues in apples. To each state of the world, the decision maker assigns a probability. Let (π_1,π_2) be the distribution over states, where π_1 is the chance of state 1 and π_2 is the chance of state 2. For the purpose of illustration, assume that the "estimated" probability distribution (y_o) of the states is (0.0001, 0.9999). That is, this distribution is the "best guess" distribution reflecting all the information the decision maker has about the probabilities of states. Table 2-3 assigns an arbitrary utility number to each outcome and then reports the expected utility (est_x) of each act. This is shown in the column labeled "est_x" in Table 2-3.

The decision maker may not have very much confidence in his/her estimated distribution of probabilities. He/she may believe that the distribution is anywhere from (0.1, 0.9) to (0.000001, 0.999999), with (0.0001, 0.9999) being the "average" probability distribution. Table 2-3 reports the min_X, which is calculated using the least desirable of these distributions [(0.1, 0.9)]. Assuming for the purpose of illustration that $\rho=0.25$, the indices for the 4 acts are shown in the column labeled "index" in Table 2-3.

Based on these figures, the decision maker would choose "some of both," while the standard expected utility model would predict that the decision maker would choose "tested apples."

Table 2-3: Ellsberg's Decision Rule in the Context of the Pesticide Residue Case Study

Act		Utility of outcome in state 1	Utility of outcome in state 2	Est_X	Min_X	Index
X_1:	buy only regular apples	$u(x_1^1)=5$	$u(x_2^1)=18$	17.999	16.70	17.02
X_2:	buy only tested apples	$u(x_1^2)=1$	$u(x_2^2)=20$	19.998	18.10	18.57
X_3:	buy some of both types of apple	$u(x_1^3)=15$	$u(x_2^3)=19$	18.999	18.60	18.70
X_4:	do not buy apples	$u(x_1^4)=0$	$u(x_2^4)=15$	15.000	15.00	15.00

Notes:

$min_X = min\pi_1\, u(x_1^X) + min\pi_2\, u(x_2^X)$ where $(min\pi_1, min\pi_2)$ is the worst possible probability distribution

$est_X = \pi_1\, u(x_1^X) + \pi_2\, u(x_2^X)$ where (π_1, π_2) is based on the "average" distribution, y_o.

$index = \rho u(est_X) + (1-\rho)u(min_X)$

The conclusions drawn from Ellsberg's (1961) analysis are that "1) certain information states can be meaningfully identified as highly ambiguous; 2) in these states, many reasonable people tend to violate the Savage axioms with respect to certain choices; 3) their behavior is deliberate and not readily reversed upon reflection; 4) certain patterns of 'violating' behavior can be distinguished and described in terms of a specified decision rule" (Ellsberg 1961, 669). This last conclusion implies that explicitly accounting for ambiguity in the model of choice may lead to choices different from those predicted by the EU model.

Gärdenfors and Sahlin (1982) follow Ellsberg's (1961) definition of ambiguity. Consider Miss Julie in Gärdenfors and Sahlin's (1982) analysis. She is deciding on which tennis match she should place a bet. She is quite familiar with both players in Match A. She has seen them play, knows their playing histories, and feels confident in her assessment that the players are so closely matched that the outcome will depend purely on luck. She knows nothing about the players in Match B. She has never seen them play, and has no information on which to make a judgement as to who will win the match. She has heard that one of the players in Match C is quite a bit better than the other and is almost sure to win, yet she does not know which player it is. It seems reasonable to expect that **if forced to bet**, Miss Julie would prefer to bet on match A.[18]

[18] It could be argued that Miss Julie should acquire more information before betting. However, under the "economics of uncertainty" in which only terminal moves are allowed, this is not a possibility.

Gärdenfors and Sahlin propose that a decision maker considers several probability distributions over states of the world. Attached to each probability distribution is a measure of its "epistemic reliability (ρ)," a measure that reflects the state of one's knowledge about a particular probability distribution. Gärdenfors and Sahlin's thesis is that an assessment of the epistemic reliability is necessary to understand the decision process.

In Gärdenfors and Sahlin's framework, ρ has an upper bound representing the case where the decision maker has perfect knowledge about the probability distribution and a lower bound where the decision maker has no knowledge at all about the probability distribution (analogous to "risk" and "ignorance" as described in chapter 1).

In this decision theory, ρ is directly related to the amount of information a decision maker has. "Where little information is available, all distributions will, consequently, have about the same degree of epistemic reliability. Conversely, in a decision situation where the agent is well-informed about the possible states of nature, some distributions will tend to have a higher degree of epistemic reliability than others" (Gärdenfors and Sahlin 1982, 367).

The decision process described by the authors has two steps. The first step is to select a class of probability measures with acceptable degrees of reliability on which a decision is to be based. Certain probability distributions over the states of nature can be ruled out as serious possibilities, even though they are "epistemically possible." Relative to this class, one can then, for each decision alternative, compute the minimal expected utility of the alternative. In the second step the alternative with the largest minimal expected utility is chosen.

The authors claim that the biggest difference from Ellsberg is that he has an estimated probability distribution over states of nature, y_o, that has the highest degree of confidence attached to it, while Gärdenfors and Sahlin say that once the set of possible distributions has been selected, "the distribution with the highest degree of reliability (corresponding to Ellsberg's (1961) y_o) does not play any outstanding role in the decision making" (Gärdenfors and Sahlin 1982, 377).

Levi (1974) also claims that decision makers do not have a single point estimate of the probability of each state of nature. A decision maker may consider more than one distribution as describing the probabilities of the states of nature. But Levi argues that these are "neither true nor false. Hence, they are neither possibly true nor possibly false. One cannot compare such distributions with respect to probability" (Levi 1982, 389). He says that to these distributions one cannot therefore assign second-order probabilities.

He also differs from the other authors presented here in the decision rule about how to pick an alternative under a situation of more than one probability distribution over states of nature. His rule is lexicographic in nature and consists of 2 steps. The decision rule may be simplified to be: for a lottery offering positive prizes, first choose the alternatives that under at least one probability distribution yields a maximal outcome (called "E-admissible"). From among these, choose the one that has the largest "worst" outcome.

The models presented in this section all depart from the expected utility model by accounting for the ambiguity of risk estimates. Similarly, they all use a measure of ambiguity that is a function of the amount and quality of information upon which risk estimates are based. They differ primarily in the way that measure is used in a decision model for choice. None of the models has axiomatic underpinnings, however, and they offer only ad hoc models of behavior.

Data-Based Models

Probability Weighting Approach[19]

Several authors have argued that ambiguity can be accounted for by using "decision weights" in the expected utility model instead of the standard point estimate probabilities of outcomes [Einhorn and Hogarth (1985,1986), Hogarth and Kunreuther (1989), Fellner (1961), Viscusi and O'Conner (1984), Viscusi and Magat (1992), Hazen (1987), Kahneman and Tversky (1979)].

These models assume that a second-order probability distribution (SOP) over probabilities exists and that the mean of that distribution, $E(\pi)$, is known by the decision maker. The decision maker "weights" his/her estimate of $E(\pi)$ in response to ambiguity.[20]

The general "decision weight" model (for the discrete case with n possible states of nature) is:

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[19] Other names for these models include: **decision weight models, probability adjustment models, and belief function models.**

[20] Where no confusion arises from doing so, $E(\pi)$ is simply written as π, or π_s when there are more than two states.

$$WEU = \sum_{s=1}^{n} w(\pi_s)u(x_s) \tag{2-4}$$

where:

WEU	=	weighted expected utility
π_s	=	the probability of state s
w	=	probability weighting function
u	=	utility function
x_s	=	outcome in state s
n	=	the number of possible states of the world

This section reviews some of the "adjusting" mechanisms (the shape of w in equation 2-4) proposed by various authors. The models vary mostly in the factors that influence the weighting function, and in how the weighting function is constructed. They are all variants of the simple probability weighting model in equation 2-4.

Einhorn and Hogarth (1985) develop a descriptive model of decision making called "anchoring and adjustment." A decision maker makes an initial assessment, π, of the probability of an outcome. He/she then adjusts this estimate up or down to reflect the ambiguity in the situation. The initial estimate may be the best estimate of experts, reflect one's previous information about a subject, or be a number that sticks in the decision maker's mind. The final judgement is $S(\pi) = \pi + k$ where k is the net effect of the adjustment process. The adjustment, k, is affected by several factors:

1. the level of π.
2. the amount of ambiguity perceived in a situation. This is denoted by θ which is between 0 and 1. The greater the ambiguity the greater the adjustment.
3. the person's attitude toward ambiguity in the circumstances. This is reflected in the tendency to give differential attention or weight to values of π that are greater or smaller than the initial estimate π. Attitude toward ambiguity is denoted by β.

After the net effect of the adjustment process has been accounted for the full model is:

$$S(\pi)=\pi+\theta(1-\pi-\pi^{\beta}) \tag{2-5}$$

In the pesticide residue survey used here, for example, π would correspond to the risk assessment solicited from respondents. To use this estimate in a choice model that accounts for ambiguity, it would have to be "revised" to account for the respondents perceived ambiguity and attitude toward ambiguity as per the equation above. The "adjusted" probability, $S(\pi)$, could then be used as a "decision weight" in the expected utility framework.

Einhorn and Hogarth (1986) present a model of choice of gamble under ambiguity. They define the concept of expected worth under ambiguity (EWA) as:

$$EWA=w_G S(\pi)+w_L S(1-\pi) \tag{2-6}$$

where w_G and w_L are the "subjective worths of the amounts to be gained and lost in a two-outcome gamble, π is the "anchor" assessment of the probability of gain, $(1-\pi)$ is the "anchor" assessment of the probability of loss, and $S(\pi)$ and $S(1-\pi)$ are the "decision weights" of gaining and losing as defined above. The decision rule is then to choose the gamble that maximizes EWA.

Hogarth and Einhorn's (1990) venture theory is similar to the anchoring and adjustment model. The decision maker is again assumed to anchor on an initial probability estimate and then adjust the estimate up or down by mentally simulating other possible values. The amount of mental simulation, or adjustment, is hypothesized to be a function of several factors including: the absolute size of the payoffs, the extent to which the anchor deviates from the extremes of 0 and 1, and the level of perceived ambiguity concerning the relevant probability.

Fellner (1961) also discusses "adjusting" probabilities in situations of ambiguity. In cases of uncertainty about probabilities, people may be unwilling to assign probabilities to complementary states of the world such that the probabilities sum to unity. One may assign a probability of 0.3 to state 1, and only 0.4 to state not-1 (Fellner calls these "uncorrected" probabilities). To deal with ambiguity, Fellner says "in general, these uncorrected probabilities need not add up to unity...We now inflate or deflate as the case may be, the uncorrected probabilities in such a way that their sum should equal unity, and that the ratio of the corrected probabilities should be the same as was that of the uncorrected ones" (Fellner 1961, 674).

Prospect theory, developed by Kahneman and Tversky (1979), also uses "decision weights" instead of probabilities in weighting the utility of outcomes. In this theory "decision weights measure the impact of events on the desirability of prospects, and not merely the perceived likelihood of these events" (Kahneman and Tversky 1979, 280). Decision weights in prospect theory are a function of the subjective probability of an outcome, but can also be affected by factors such as ambiguity. This model allows low probabilities to be overweighted ($w(\pi) > \pi$ for small π) and large probabilities to be underweighted ($w(\pi) < \pi$ for large π). The authors also claim that there is evidence to suggest that for all $0 < \pi < 1$, $w(\pi) + w(1-\pi) < 1$. This is called subcertainty and it suggests that if small probabilities are overweighted, large probabilities are underweighted.

Hazen (1987) presents a completely axiomatized probability weighting model called "Subjectively Weighted Linear Utility (SWLU)." In this model, the subjective probability of an outcome is weighted by the **desirability** of the outcome relative to the other possible outcomes.

The SWLU of an act is:

$$SWLU = \frac{\sum_{s=1}^{n} \pi_s \psi[u(x_s)] u(x_s)}{\sum_{s=1}^{n} \pi_s \psi[u(x_s)]} \tag{2-7}$$

where:

SWLU	=	subjectively weighted linear utility
π_s	=	the probability of state s
ψ	=	a function that weights π_s based on the utility of the outcome in state s
u	=	utility function
x_s	=	outcome in state s
n	=	the number of possible states of the world

Another way to account for ambiguity is by allowing non-additive probabilities in the EU (Schmeidler 1989) and the SEU (Gilboa 1987). In these models, the probability of two equally likely complementary states need not sum to unity. If π_1 is the probability of state 1, π_2 is the probability of state 2, and π_1 and π_2 do not sum to unity, then $1-\pi_1-\pi_2$ measures the "faith" in π_1 and π_2.

An unappealing feature of the probability weighting models is that they generally violate first order stochastic dominance, i.e., dominated choices may be chosen over dominating choices. If dominance is **not** violated, probability weighting models collapse back to the EU model.

The following example of how the probability weighting model violates dominance rules is borrowed from Weber and Camerer (1987).

Suppose a decision maker can choose to bet on one of two lotteries: X_1 and X_2. The lottery X_1 is defined as: $X_1=(x_1, \pi; 0, 1-\pi)$ where x_1 is some positive payoff, and π is the probability of receiving outcome x_1. Suppose further that π can be written as the sum of two probabilities (i.e., $\pi=\pi^o+\pi^1$). The lottery X_1 can then be written as $X_1=(x, \pi^o+\pi^1; 0, 1-\pi^o-\pi^1)$. The lottery X_2 is defined as: $X_2 =(x+\delta, \pi^o; x, \pi^1; 0, 1-\pi^o-\pi^1)$. Lottery X_2 is derived from lottery X_1 by adding a small payoff, δ, with probability π^o to lottery X_1. Lottery X_2 stochastically dominates lottery X_1 since one should always prefer lottery X_2. If the decision maker uses a probability weighting model to evaluate these lotteries, X_1 will be preferred to X_2, which is a violation of first-order stochastic dominance. Suppose the decision maker uses the model proposed by Handa[21] (1977) in which

$$WEU = \sum_{s=1}^{n} w(\pi_s)x_s \tag{2-8}$$

where:

WEU	=	weighted expected utility
π_s	=	the probability of state s
w	=	probability weighting function
x_s	=	outcome in state s
n	=	the number of possible states of the world

If $w(\pi^o+\pi^1)>w(\pi^o)+w(\pi^1)$ then there is a sufficiently small δ such that

[21] This model is used here only for purposes of illustration. The same result would follow from any of the simple probability weighting models described in this section.

$$w(\pi^0 + \pi^1)x \; > \; w(\pi^0)(x+\delta) + w(\pi^1)x \tag{2-9}$$

Lottery X_1 will result in a higher utility level than lottery X_2, even though X_2 stochastically dominates X_1.

As Weber and Camerer (1987) point out, a descriptive theory should be able to account for violations in stochastic dominance but not predict them in a wide variety of situations.

Theoretical Models

Non-Linear Weighting of Second-Order Probability Distributions

Although the probability models just described assume a SOP around the probabilities of outcomes, they apply weights to only the expected probability ($E(\pi)$) of the SOP to account for ambiguity. As such, they lead to violations of stochastic dominance and can lead to sub- or super-certainty. Another class of models applies non-linear decision weights to the entire SOP. These models are able to account for ambiguity without violating first-order stochastic dominance.

Kahn and Sarin (1988) present a variant of the probability weighting model for predicting consumers' choices under ambiguity in which the probability of an outcome is a function of the entire SOP. If the probability density function (SOP) for π is $\phi(\pi)$, the decision weight is defined as follows:

$$w(\pi) = E(\pi) + \int_{\pi=0}^{1} (\pi - E(\pi)) e^{[-\lambda(\pi - E(\pi))]/\sigma} \phi(\pi) \, d\pi \tag{2-10}$$

where:

$E(\pi)$	=	the expected value of the probability of an outcome
$\phi(\pi)$	=	the probability density function of π
λ	=	reflects an individual's attitude toward ambiguity in a given context

and

$$\sigma = \sqrt{\int_{\pi=0}^{1} (\pi - E(\pi))^2 \phi(\pi) d\pi} \tag{2-11}$$

is the standard deviation of the random variable π.

This model departs from the SEU by assigning a **non-linear** decision weight to the probability of an outcome. If there is no ambiguity then $w(\pi)=E(\pi)$ and the model reduces to the SEU. Similarly, if the individual is ambiguity neutral ($\lambda=0$), then again $w(\pi)=E(\pi)$ and the model reduces to SEU. This model differs from the probability weighting models discussed in the previous section in that the decision weight $w(\pi)$ is a function of the entire second-order probability distribution, $\phi(\pi)$, and not just of the mean of the distribution.

The Rank-Dependent Expected Utility Model (RDEU)

The Rank-Dependent Expected Utility Model (RDEU), developed by Quiggin (1982), uses a nonlinear weight of the entire probability distribution over **outcomes** (although not over probabilities of outcomes). Segal (1987) modifies this model by allowing for nonlinear weighting of the SOP.

Because the RDEU is the basis for Segal's (1987) approach to modeling decision making under ambiguity, it will be reviewed here. Without Segal's modification, however, the RDEU does not explicitly accommodate ambiguity. RDEU is an extension of the simple probability weighting model (described above) to multiple outcomes. It is a generalized utility model that maintains several of the features of the expected utility model (transitivity, completeness, continuity, and first-order stochastic dominance). The model was developed to help explain empirical violations to expected utility such as Allais' Paradox, and the systematic overweighting of small probabilities and underweigthing of large probabilities.

As in the probability weighting models, the RDEU uses "decision weights" instead of objective probabilities of outcomes. In the RDEU, however, the decision weight of the probability (π_k) of outcome x_k depends on the probabilities ($\pi_s \; \forall \; s=1...n$, $s \neq k$) of the other possible outcomes ($x_s \; \forall \; s=1...n$, $s \neq k$) and the rank, or desirability, of outcome x_k relative to all other x_s. If the lottery X offers n outcomes (i.e., outcomes x_s where $s=1...n$), and the outcomes can be ranked in order of preference ($x_1 < ...x_s < ...x_n$), the RDEU takes the following form:

$$RDEU = V(X) = \sum_{s=1}^{n} h_s(\pi)u(x_s) \tag{2-12}$$

where:

$$h_s(\pi) = f(\sum_{j=1}^{s} \pi_j) - f(\sum_{j=1}^{s-1} \pi_j) \tag{2-13}$$

π = the vector of probabilities ($\pi_1, \pi_2, ... \pi_n$) of other outcomes and the function f "transforms" the probability (which always lies between 0 and 1) such that the transformed probability remains between 0 and 1 (i.e., $f[0,1] \rightarrow [0,1]$). It is assumed that $f(0)=0$ and $f(1)=1$.

The decision maker chooses the act X that has the highest RDEU.

Incorporating Ambiguity into the RDEU

Although the RDEU allows for the over- and underweighting of the probabilities of outcomes, it does not account explicitly for ambiguity. Segal incorporates ambiguity into the RDEU model by assuming that choices involving ambiguous probabilities are like two-stage lotteries. The first-stage lottery is over the probability of an outcome; the second stage is the lottery over outcomes, using the result of the first stage as the relevant probability. This is consistent with the notion that ambiguity can be conceptualized as a second-order probability distribution (the probability distribution over probabilities).

For our apple consumer, for example, the first-stage lottery would be a lottery over the probability that an adverse outcome would result someday because of pesticide residues in food; the second-stage lottery would be the lottery over the health outcome, using the result of the first-stage lottery as the probability.

Assume a decision maker faces the following two-outcome lottery:

$$X = (x, \pi;\ 0, 1-\pi) \tag{2-14}$$

Now assume that π is itself a random variable $\tilde{\pi}^g$ where $g=1...m$ (m is the total number of possible probabilities of a given outcome). The probability that the actual probability of outcome x is π^s is q^s. That is, the probability that the lottery one will face is actually (x, π^s; 0, 1-π^s) is q^s. The different lotteries that the individual might face are the following:[22]

X_1:	$(x,\pi^1; 0,1-\pi^1)$	where $P(\pi^1) = q^1$
X_2:	$(x,\pi^2; 0,1-\pi^2)$	where $P(\pi^2) = q^2$
.	.	.
.	.	.
.	.	.
X_m:	$(x,\pi^m; 0,1-\pi^m)$	where $P(\pi^m) = q^m$

The standard approach to evaluating this lottery is to use the Reduction of Compound Lotteries Axiom (RCLA)[23]:

The Reduction of Compound Lotteries Axiom (for two outcomes):

Let X_i be a one-stage two-outcome lottery: $X_i=(x^i, \pi^i; 0, 1-\pi^i)$, i = 1,...m. Let A be a two-stage lottery in which the possible prizes are tickets to the one-stage lotteries above (X_i). Define R(A) as the one-stage lottery that is the actuarial equivalent of the combination of X_i and A (i.e., R(A) is derived by combining the probability of winning a ticket to the lottery with the probability of getting the prize once the lottery is played).

$R(A) = (x, \sum_{i=1}^{m}\pi^i q^i; 0, 1-\sum_{i=1}^{m}\pi^i q^i)$. By definition, this reduces to the same lottery as

[22] Reminder: in this lottery, there are only two outcomes, x and 0. The probability of outcome x may take one of m possible values, however. That is, the probability of receiving outcome x may take any one of $\pi^1 \ldots \pi^m$ values.

[23] For simplicity, the RCLA is stated only for the two-outcome case. For the general version of the RCLA, see Segal (1990).

equation 2-14. The decision maker is thus indifferent between the two-stage lottery A and the one-stage lottery R(A).[24]

Even in the presence of ambiguity, if one uses the RCLA in processing multiple layers of risk, ambiguity falls out of the model and is behaviorally insignificant.

Segal assumes that instead of using the RCLA, decision makers adhere to the Compound Independence Axiom (CIA) which is stated as follows:

Compound Independence Axiom: Let A be a two-stage lottery: $A=(X_1,q^1;\ldots X_m,q^m)$ and define $CE(X_i)$ by $(CE(X_i),1)\sim X_i$.[25] This notation says the decision maker is indifferent between getting the certainty equivalent of the X_i lottery ($CE(X_i)$) and facing the lottery X_i. The decision maker is then also indifferent between facing lottery A and facing the lottery $((CE(X_1),1),q^1;\ldots(CE(X_m),1),q^m)$.[26] Consider our apple consumer. He/she might be indifferent, for example, between a situation in which the probability of experiencing an adverse health outcome because of pesticide residues is somewhere between 0.1 and 0.00001, with an average probability of 0.050005, and the situation in which he/she knows for certain that the probability is 0.07.

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[24] The same conclusion would be reached if there were more than two outcomes in the one-stage lottery.

[25] The lottery $(CE(X_i),1)$ is a degenerate lottery in which the decision maker receives $CE(X_i)$ with certainty.

[26] The RCLA and the CIA together imply the Mixture Independence Axiom (MIA) which states that for every one-stage lottery X, Y, and Z, and for $\alpha \in [0,1]$, $X \succeq Y$ if and only if $\alpha X + (1-\alpha) Z \succeq \alpha Y + (1-\alpha)Z$. The MIA implies that the preference functional is linear in its probabilities. By dropping the RCLA but maintaining the CIA, we retain the spirit of the independence axiom while rejecting the assumption that a two-stage lottery is equally as desirable as its one-stage actuarial equivalent.

If there is a "certainty equivalent" for each first-stage lottery above then:

$$u[CE(X_i)] = [V(X_i)] \tag{2-15}$$

Solving equation 2-15 for $CE(X_i)$ yields:

$$CE(X_i) = u^{-1}[V(X_i)] \tag{2-16}$$

Now substitute $u^{-1}[V(X_i)]$ into the RDEU in which there are only two outcomes (x and 0) to the lottery X_i and assume $u(0)=0$. This yields:[27,28]

$$\begin{aligned} RDEUWA = V(X) &= u(x,M)\,\bar{f}(\pi^1) \\ &+ u(x,M)\sum_{i=2}^{m}[\bar{f}(\pi^i) - \bar{f}(\pi^{i-1})]\bar{f}(\sum_{g=i}^{m} q^g) \end{aligned} \tag{2-17}$$

where:

RDEUWA	=	Rank-Dependent Expected Utility with Ambiguity
u	=	utility function
x	=	outcome
M	=	income
π^i	=	the i^{th} possible probability of outcome x
$\underline{q}^g$	=	the probability that π^g is the actual probability of outcome x
f	=	the probability transformation function
m	=	the number of possible values that γ^i can take

[27] The RDEU uses the transformation function, f, when π is the probability of a "good" outcome. The transformation function when π is the probability of a "bad" outcome is $\bar{f}$ which is equal to $1-f(1-\pi)$ (Segal 1987). Since we solicited survey respondents for the probability of an adverse health effect from pesticide residues in food (a "bad" outcome) we use the transformation function $\bar{f}$.

[28] Outcome x represents some general outcome which may have several components. In Chapter 3 we specify the multiple outcomes associated with choosing a specific type of apple.

Each π^i can alternatively be written as a deviation from the mean probability of an outcome, π (Segal 1987):

$$\pi^i = \pi + \gamma^i \epsilon \qquad (2\text{-}18)$$

where:

π^i	=	the i^{th} probability of outcome x
π	=	the mean probability of outcome x
γ^i	=	a measure of the distance between π and π^i. The term γ^i varies with the possible probabilities. It does **not** vary by person.
ϵ	=	a measure of the distance between π and π^i. The term ϵ varies by person, but does **not** vary with the individual probabilities.

Together, γ^i and ϵ determine the spread of the SOP. The term ϵ varies by individual, while the term γ^i varies with the possible probabilities. To conform to the laws of probability, the following restrictions must also hold:

1) $0 < \gamma^i \epsilon < 1$

2) $0 \leq \pi - \gamma^i \epsilon \leq 1$

Since only π and ϵ vary by person, ϵ is as a measure of the perceived ambiguity around π. The higher ϵ, the higher the perceived ambiguity.

When the RDEU incorporates the probabilities written in terms of deviations from the mean we get:

$$\begin{aligned} RDEUWA = {} & u(x,M)\bar{f}(\pi + \gamma^1\epsilon) \\ & + u(x,M)\sum_{i=2}^{m}[\bar{f}(\pi + \gamma^i\epsilon) - \bar{f}(\pi + \gamma^{i-1}\epsilon)]\bar{f}(\sum_{g=i}^{m} q^g) \end{aligned} \qquad (2\text{-}19)$$

where:

u	=	utility
x	=	outcome
M	=	income

π	=	the mean probability of an outcome
ϵ	=	a partial measure of the distance between π and π^i. The term ϵ varies by person, but does **not** vary with the individual probabilities.
γ^i	=	a measure of the distance between π and π^i. The term γ^i varies with the possible probabilities. It does **not** vary by person.
q^g	=	the probability that the gth probability is the actual probability
$\bar{f}$	=	the transformation function on the probabilities
m	=	the number of possible values that γ^i can take

The two-stage lottery, where the first stage is over the possible probabilities, is now represeneted by a one-stage lottery by using the Compound Independence Axiom (certainty equivalents). The resulting objective function then depends not only on the mean probability of the outcome, but also on the perceived ambiguity about that probability. The objective function also depends on individual preferences toward ambiguity, i.e., on the shape of the transformation function, $\bar{f}$. If $\bar{f}$ is linear, the individual is ambiguity neutral (he/she doesn't care if the probabilities are certain or uncertain). In this case, the objective function reduces to the RDEU. If $\bar{f}$ is concave, people are ambiguity averse. If $\bar{f}$ is convex, people are ambiguity lovers. When deciding between alternative "ambiguous" acts or lotteries, the decision maker maximizes RDEUWA.

Segal's approach to incorporating ambiguity into the RDEU model maintains the spirit of the independence axiom by using the compound independence axiom, but drops the reduction of compound lotteries axiom. The preference functional is then nonlinear in the probabilities. This research uses Segal's model of decision making under ambiguity to analyze the factors affecting willingness to pay for pesticide-residue certification when risks are ambiguous. The next chapter describes how this model is used to describe the choice scenario facing consumers when they buy apples that may contain pesticide residues.

Measuring Ambiguity

There are three ways described in the literature for measuring ambiguity: (1) using the "range" of the possible probabilities of outcomes, (2) using the variance of the SOP, and (3) by the degree of confidence one feels in one's risk estimate. The next section reviews these approaches and discusses the measure used in this research.

Range

Becker and Brownson (1964) and Curley and Yates (1985) use the "range" of the possible probabilities of outcomes as a way of measuring the amount of ambiguity present in a choice situation. As is consistent with the discussion of ambiguity above, one has an estimate of the probability of an outcome, but several other probabilities may also be possible. The distance from the lowest of these other possible probabilities to the highest is the "range" of probabilities and is considered a measure of the amount of ambiguity present.

The authors claim that this approach can be used to quantify Ellsberg's notion of the degree of confidence one has in a probability estimate. Ambiguity is directly associated with the length of the range of possible probabilities of states of nature - the shorter the range, the lower the ambiguity. The difference in ambiguity between two options is defined as the absolute difference between the ranges. The Ellsberg urn that has 50 red and 50 black balls has a range of zero, and therefore no ambiguity about the probabilities of states of nature. The urn that has 100 balls in unknown proportions, on the other hand, has a range of 100, and therefore maximal ambiguity (ignorance). This approach assumes that the probability distribution over probabilities is a uniform distribution where each probability has the same probability of being the true probability.

The Variance of the Second-Order Probability Distribution

The "range" measure of ambiguity differs from the variance of the probability distribution over probabilities because the range measures merely the distance from one endpoint of the distribution to the other and assumes that the distribution is a uniform distribution over probabilities. The variance of the probability distribution over probabilities, on the other hand, takes into account the shape of the distribution (Kahn and Sarin 1988). The variance of a beta distribution, for example, will be different from the variance of a uniform distribution, even though their "ranges" may be the same. Theoretically, the variance is the appropriate measure of ambiguity; in practice it is difficult to ascertain the shape of the probability distribution over probabilities.

Degree of Confidence

The degree of confidence approach (Ellsberg 1961; Gärdenfors and Sahlin 1982, 1983) assumes there is a confidence interval around the mean probability of an outcome. Confidence, then, is an indicator of the "spread" of the probability distribution around the probability. The higher the confidence, the smaller the confidence interval.

Confidence can be measured in terms of a probability ("I am 95% sure that the probability of outcome x is 0.75") or in qualitative terms ("I am 'very sure' that the probability of outcome x is 0.75).

Ambiguity in this research is represented by ϵ in equation 2-19. It is a parameter partly determining the distance between the mean probability and all other possible probabilities. To measure ϵ, the survey asked respondents how sure they were about their estimate of the probability of an adverse health outcome. A Likert scale (1=very sure, 2=somewhat sure, 3=somewhat unsure, 4=very unsure) was used to measure confidence in risk estimates.

Conclusions and Observations

Ambiguity is defined as uncertainty about the probability of an outcome. In situations of ambiguity, the probability of an outcome becomes a random variable. Traditional models of decision making under risk cannot account for ambiguity as they use point estimates of probabilities to evaluate choices. Attempts to incorporate ambiguity into expected utility models fail mainly because of violations of stochastic dominance. The RDEU is a generalized utility model that can be modified to account explicitly for ambiguity about the probabilities of outcomes. Generalized utility models are desirable because they maintain completeness, transitivity, continuity, independence, and first-order stochastic dominance.

Following Segal (1987), this research assumes that situations of ambiguity are like 2-stage lotteries in which the first stage is a lottery over the probability, and the second stage is a lottery over the outcome. When making decisions concerning two-stage lotteries, Segal assumes that decision makers do not necessarily use the Reduction of Compound Lotteries Axioms (i.e., a two-stage lottery is not necessarily equivalent to its one-stage actuarial equivalent). Instead, certainty equivalents are used to convert a two-stage lottery to a one-stage lottery. Segal uses these assumptions to modify the RDEU to account explicitly for ambiguity. Ambiguity then enters peoples' objective function in two ways: 1) through the perceived amount of ambiguity and 2) through the individual's attitude toward ambiguity (the shape of the weighting function, $\bar{f}$). This research assumes that decision makers are ambiguity averse ($\bar{f}$ is concave) so that they prefer known to unknown probabilities. Ambiguity has the effect of increasing the overall riskiness of a prospect, but its effect on decisions is distinct from standard risk aversion because of the shape of the weighting function.

The next chapter uses Segal's (1987) model to develop hypotheses about consumers' willingness to pay for pesticide residue certification, the effect of baseline risk and ambiguity and changes in risk and ambiguity on willingness to pay for certification when risks are ambiguous.

CHAPTER 3: CONCEPTUAL FRAMEWORK

This research attempts to determine the effect of risk and ambiguity about risks on consumers' willingness to pay (WTP) for pesticide-residue certification. It uses the case study of consumer demand for apples that are certified to have met certain standards for pesticide residues to examine the effect on WTP for certification of (1) consumers' perceptions of the **baseline** risk and ambiguity associated with pesticide residues on regular apples and (2) consumers' perceptions of the **changes** in risk and ambiguity that result when one chooses certified rather than regular apples.

This chapter first describes the choice problem the consumer faces when deciding between regular and certified apples. It then presents a choice framework based on Segal's (1987) model that modifies the choice problem when decisions are made under ambiguity. The chapter then develops hypotheses about the value of certification and the effect of both **baseline** and **changes in** risk and ambiguity on willingness to pay for certification. The chapter concludes with a discussion of the use of ordinary consumer surplus to measure the total value of the certification.

Consumers' Choice Problem

Although consumers cannot pay **directly** to reduce the ambiguity or risks from pesticide residues in food, they can make market choices that affect both the risks they face and the ambiguity they experience. From these choices we can infer the effect of risk and ambiguity on WTP for certification.

When consumers buy apples, they must make two types of decisions: which type of apple to buy, and how many apples. Assume that consumers may buy regular apples at price p_r per pound or apples that have been tested and certified to meet certain standards for pesticide residues at price p_c per pound.[29,30] The regular and the certified apples are identical except for their price and the certification about pesticides. Apples with different levels of residues are differentiated qualities of the same product; the choice between regular and certified apples is then a choice between two brands (regular and certified) of the same product (apples) that have a different quality dimension (different levels of pesticide residues) (Hanemann 1982).[31] Each brand of the good is a separate commodity; the consumer selects the quality of the good implicitly by choosing a particular brand.

When the decision maker consumes the regular apples, he/she perceives there to be some probability (π^r) of experiencing an adverse health outcome someday from the

[29] The contingent valuation survey used to simulate this choice scenario is described in the next chapter.

[30] In the contingent valuation survey, half of the respondents were asked to choose between regular apples and apples that have been tested and certified to have been *produced without pesticides*; the other half was asked to choose between regular apples and apples that are tested and certified to *meet federal standards for pesticide residues*.

[31] Only the pesticide residue level is considered a characteristic of apples. Individual perceptions of the risk and ambiguity associated with pesticide residue levels are not themselves characteristics of apples.

pesticide residues on those apples.[32] When the consumer chooses the certified apple instead, the perceived probability of the same adverse health outcome is π^c.[33]

The standard analysis of consumers' willingness to pay for reduced risk (Jones-Lee 1974) assumes that π^r and π^c are known with certainty; the value of the certification then derives solely from the risk reduction it offers. As described in Chapter 1, however, consumers are often uncertain about the risks they face from pesticide residues in food. The probability of an adverse health outcome in the case of uncertainty is a random variable; ϵ is a measure of the spread of the probability distribution around the mean probability (ϵ^r is the ambiguity associated with π^r, ϵ^c is the ambiguity associated with π^c). When the consumer buys the certified apple, he/she may be buying not only reduced risk, but may also be buying reduced ambiguity.[34,35]

When the decision maker buys apples, he/she implicitly chooses the risk and ambiguity levels by the type of apple he/she chooses. By choosing regular apples, he/she chooses a risk level of π^r and an associated ambiguity level of ϵ^r; by choosing certified apples, he/she chooses a risk level of π^c and ambiguity level of ϵ^c.

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[32] This study does not specifically define an "adverse health outcome from pesticide residues." It is whatever the respondent thinks is the most likely health outcome, were one to occur.

[33] We assume that $\pi^c \leq \pi^r$. The perceived risk from pesticide residues when food is certified is presumably no larger the risk when food is not certified.

[34] This is true if ambiguity is due to uncertainty about the presence of residues. However, if ambiguity is due to uncertainty about the toxicity of residues, buying certified apples may not reduce ambiguity.

[35] The consumer may be buying other things as well such as reduced health risks to farm workers, reduced groundwater contamination from pesticides, etc. Future research should explore the value of these other benefits.

As mentioned earlier, the consumer must choose both the "brand" and the quantity of apples when making a purchase decision. Although these decisions may generally be made at the same time, they can be separated into two steps. When deciding on the total quantity of apples, the decision maker maximizes the following:

$$U = u(y, x^r, x^c, \pi^r, \epsilon^r, \pi^c, \epsilon^c) \tag{3-1}$$

subject to the budget constraint:

$$p_r x^r + p_c x^c + p_y y = M \tag{3-2}$$

where:

x^r	=	pounds of regular apples consumed
x^c	=	pounds of certified apples consumed
p_r	=	the per-pound price of regular apples
p_c	=	the per-pound price of certified apples
y	=	Hicksian composite good other than apples
p_y	=	the price of the Hicksian composite good
π^r	=	the probability of an adverse health effect resulting from pesticide residues in food when the decision maker chooses regular apples
π^c	=	the probability of an adverse health effect resulting from pesticide residues in food when the decision maker chooses certified apples
ϵ^r	=	the ambiguity about π^r, an indicator of the spread of the probability distribution around the mean probability
ϵ^c	=	the ambiguity about π^c, an indicator of the spread of the probability distribution around the mean probability
M	=	income

The indirect utility function is obtained by substituting the optimal quantities demanded from this maximization problem into the utility function. The indirect utility function is:

$$V = v(p_r, p_c, p_y, \pi^r, \pi^c, \epsilon^r, \epsilon^c, M) \qquad . \qquad (3\text{-}3)$$

When the consumer chooses between brands (regular or certified), the decision rule is to choose the brand that produces the highest indirect utility (quantity having already been maximized).

As was demonstrated in Chapter 2, if all the assumptions and postulates of expected utility hold, the general utility and indirect utility function can be represented by the preference functional of the expected utility. In this formulation of the consumer choice problem, ambiguity is behaviorally insignificant.

This research assumes that when the consumer chooses the brand of apples he/she is facing a choice situation similar to a two-stage lottery. The first stage is a lottery over the **probability** that an adverse health outcome will result someday because of pesticide residues in apples; the second stage is over the actual health **outcome** that results from pesticide residues in food.

In determining the preference functional that consumers use to make choices concerning this two-stage lottery they face, this research follows Segal (1987) and assumes that when assessing the probabilities of various states in the presence of ambiguity, the decision maker does not use the Reduction of Compound Lotteries Axiom (RCLA) but rather uses the Compound Independence Axiom (CIA).[36] As shown in Chapter 2, a two-stage lottery is then not necessarily equally as desirable as its one-stage actuarial equivalent. The decision maker is assumed to maximize the RDEUWA described in Chapter 2.

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[36] These axioms are presented in detail in Chapter 2.

The consumer chooses the quantity of regular apples that maximizes the following:

$$RDEUWA = u_h(y,x^r,x^c,M)\bar{f}(\pi^r + \gamma^1\epsilon^r) + u_h(y,x^r,x^c,M)\sum_{i=2}^{m}[\bar{f}(\pi^r + \gamma^i\epsilon^r) - \bar{f}(\pi^r + \gamma^{i-1}\epsilon^r)]\bar{f}(\sum_{j=i}^{m} q^j) \tag{3-4}$$

and the quantity of certified apples that maximizes the following:

$$RDEUWA = u_h(y,x^r,x^c,M)\bar{f}(\pi^c + \gamma^1\epsilon^c) + u_h(y,x^r,x^c,M)\sum_{i=2}^{m}[\bar{f}(\pi^c + \gamma^i\epsilon^c) - \bar{f}(\pi^c + \gamma^{i-1}\epsilon^c)]\bar{f}(\sum_{j=i}^{m} q^j) \tag{3-5}$$

where:

u_h	=	utility in the state of the world in which one experiences an adverse health effect because of pesticide residues in apples
x^r	=	pounds of regular apples consumed
x^c	=	pounds of certified apples consumed
y	=	Hicksian composite good other than apples
M	=	income
π^r	=	the probability of an adverse health effect resulting from pesticide residues in food when the decision maker chooses regular apples
π^c	=	the probability of an adverse health effect resulting from pesticide residues in food when the decision maker chooses certified apples
ϵ^r	=	the ambiguity about π^r, an indicator of the spread of the probability distribution around the mean probability
ϵ^c	=	the ambiguity about π^c, an indicator of the spread of the probability distribution around the mean probability
γ^i	=	a measure of the distance between π and π^i. The term γ^i varies with the possible probabilities. It does not vary by person.
q^j	=	the probability of the probability

$\bar{f}$ = the transformation function on the probabilities[37]
m = the number of possible values that γ^i can take

When deciding among "brands," the decision maker chooses the brand that yields the highest indirect expected utility. That is the decision maker chooses between:

$$RDEUWA = v_h(p_y,p_r,p_c,M)\bar{f}(\pi^r + \gamma^1\epsilon^r) + v_h(p_y,p_r,p_c,M)\sum_{i=2}^{m}[\bar{f}(\pi^r + \gamma^i\epsilon^r) - \bar{f}(\pi^r + \gamma^{i-1}\epsilon^r)]\bar{f}(\sum_{j=i}^{m} q^j) \tag{3-6}$$

for regular apples, and

$$RDEUWA = v_h(p_y,p_r,p_c,M)\bar{f}(\pi^c + \gamma^1\epsilon^c) + v_h(p_y,p_r,p_c,M)\sum_{i=2}^{m}[\bar{f}(\pi^c + \gamma^i\epsilon^c) - \bar{f}(\pi^c + \gamma^{i-1}\epsilon^c)]\bar{f}(\sum_{j=i}^{m} q^j) \tag{3-7}$$

for certified apples.[38]

The Value of Certification When Risks are Ambiguous

The Value of Certification

This section reviews the Jones-Lee approach to valuing risk reduction and shows how this technique can be applied to the choice framework when risks are ambiguous, as just outlined, to obtain the value of residue certification when risks are ambiguous.

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[37] Segal (1987) uses the notation $f(\pi)$ for the transformation function on π when the outcome is desirable. When the outcome is a negative outcome, the transformation function is $\bar{f} = 1 - f(1-\pi)$. To maintain consistency with his approach, this study uses the same notation.

[38] v_h is the indirect utility in the state of the world in which one experiences an adverse health outcome because of pesticide residues in apples.

Jones-Lee (1974) uses the expected utility framework with state-dependent utilities to evaluate willingness to pay for risk reduction.[39] Consider two states of the world: "life" and "death."[40] The utility of wealth, W, if "life" prevails is L(W); D(W) is the utility if "death" occurs. If π is the probability of "death" and $(1-\pi)$ the probability of "life," then the decision maker chooses the act that maximizes the mathematical expectation of utility given by:

$$EU=(1-\pi)L(W)+\pi D(W) \tag{3-8}$$

If an individual's initial wealth is W^{o} (>0) and he/she faces an initial probability π^{o} ($0<\pi^{o}<1$) of death during the current period, his/her expected utility is:

$$E(U)=(1-\pi^{o})L(W^{o})+\pi^{o}D(W^{o}) \tag{3-9}$$

where $L(W^{o})$ and $D(W^{o})$ denote, respectively, L(W) and D(W) evaluated at $W=W^{o}$.

If the individual is offered the opportunity to reduce the probability of death during the current period from π^{o} to π^{1} (where $\pi^{1}<\pi^{o}$), he/she should be willing to pay some amount to face the new probability. This amount is the compensating variation (CV) and is defined as the amount of money that will leave the decision maker with the

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[39] This type of model is also used by other researchers. See, for example, Viscusi, Magat, and Huber (1987). Smith and Desvouges (1987) amend the model by considering a two-stage process in which the individual has a risk, R, of being exposed to hazardous wastes during the time horizon described by the model and, if exposed, a separate risk, q, of premature death from the exposure.

[40] This model can also be used to model the demand for risk reduction when the "states of the world" are "no health outcome" and "health outcome," as in this research. To be consistent with Jones-Lee (1974), however, the presentation of the model will use the states "life" and "death."

same level of expected utility as in the initial situation. CV will thus satisfy the following equation:

$$(1-\pi^1)L(W^o-CV)+\pi^1 D(W^o-CV)=(1-\pi^o)L(W^o)+\pi^o D(W^o) \tag{3-10}$$

CV is the Hicksian compensating variation in wealth for a change in probability from π^o to π^1.

The compensating variation in the case of ambiguous risks is the amount of income the decision maker is willing to give up in exchange for a reduction in probability from π^r to π^c and a reduction in the ambiguity from ϵ^r to ϵ^c. That is, CV is the amount the decision maker is willing to pay for the certification. It satisfies the following equation:

$$\begin{aligned}
& v(p_y,p_r,p_c,M-CV)\bar{f}(\pi^c+\gamma^1\epsilon^c) \\
& + v(p_y,p_r,p_c,M-CV)\sum_{i=2}^{m}[\bar{f}(\pi^c+\gamma^i\epsilon^c)-\bar{f}(\pi^c+\gamma^{i-1}\epsilon^c)]\bar{f}(\sum_{j=i}^{m}q^j) \\
& = \\
& v(p_y,p_r,p_c,M)\bar{f}(\pi^r+\gamma^1\epsilon^r) \\
& + v(p_y,p_r,p_c,M)\sum_{i=2}^{m}[\bar{f}(\pi^r+\gamma^i\epsilon^r)-\bar{f}(\pi^r+\gamma^{i-1}\epsilon^r)]\bar{f}(\sum_{j=1}^{m}q^j)
\end{aligned} \tag{3-11}$$

From this model, we develop hypotheses about the effect of baseline and changes in risk and ambiguity on willingness to pay for residue certification.

The Effect of Changes in Risk on WTP for Certification

The change in WTP for certification due to a change in mean risk is represented by $-(\partial CV/\partial \pi^c)$.[41] This expression evaluated at $\pi^c = \pi^r$ is the marginal value of an decrease in risk from the initial level (Jones-Lee 1974).[42] We use equation 3-11 to find this expression. If consumers are ambiguity averse (i.e., the transformation function, $\bar{f}$, is concave)[43], and if ambiguity is unaffected by changes in the mean risk and the marginal utility of income is positive, equation 3-11 can be used to show that in situations of ambiguous risks:

$$- \left[\frac{\partial CV}{\partial \pi^c} \right]_{\pi^r} > 0 \qquad (3\text{-}12)$$

where $\left[\frac{\partial CV}{\partial \pi^c} \right]_{\pi^r}$ indicates that the expression is evaluated at π^r.

We thus have the following hypothesis:

Hypothesis 1. The marginal value of a decrease in the mean probability of an adverse health outcome (when ambiguity present) is positive

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[41] In this particular case $\partial \pi^c = \pi^r - \pi^c$.

[42] Note that this is the marginal value of a *decrease* in risk and is therefore positive. By contrast $(\partial CV/\partial \pi^c)$ is the marginal value of an *increase* in risk (Jones-Lee 1974).

[43] Given the plethora of empirical results demonstrating that in most situations people do not like ambiguity, and given the serious nature of the possible health effects from pesticide residues, these are reasonable assumptions. There are some situations, however, in which people systematically prefer ambiguity to no ambiguity. These are situations characterized by very small probabilities of very large gains. See Segal (1987, 187) for examples. The assumption of ambiguity aversion should be explored further.

This calculation is the shown in Appendix 3-1. As in the case when risks are not ambiguous, the amount consumers are willing to pay to reduce risks should increase with the amount of risk reduction they obtain (regardless of the level of ambiguity).

The Marginal Value of Changes in Ambiguity

Segal (1987) shows using the RDEUWA that a less ambiguous lottery has a higher value (in terms of the RDEUWA) than a more ambiguous lottery. He also shows that a non-ambiguous lottery has more value than an ambiguous one.[44] Using the general formulation for utility, this can also be written as:

$$u^o = v(p_y, p_c, p_r, \pi^r, \epsilon^r, M) < v(p_y, p_c, p_r, \pi^r, \epsilon^c, M) = u^1 \tag{3-13}$$

where:

$\epsilon^c < \epsilon^r$.

Segal (1987) shows that this holds provided the following assumptions about the probability transformation function hold:

[44] These two statements are not synonymous. Segal (1987) shows that it is not generally true that because the no ambiguity situation is preferred to the ambiguous situation that less ambiguity is in general preferred to more. See Segal (1987, 189-191) for details.

1) the transformation function, $\bar{f}$, is concave;

2) $\dfrac{\pi \bar{f}'(\pi)}{\bar{f}(\pi)} \leq 0$

3) $\dfrac{\pi f'(\pi)}{f(\pi)} \geq 0$

4) $\dfrac{\bar{f}''}{\bar{f}'} \geq 0$

If equation 3-13 holds, then there must be some positive amount of money (CV) that can be taken away from the consumer such that he/she is indifferent between the situation with higher ambiguity and income M, and lower ambiguity and income (M-CV), holding mean risk constant at π^r. That is, there is some positive amount, CV, that solves the following:

$$u^o = v(p_y, p_c, p_r, \pi^r, \epsilon^r, M) = v(p_y, p_c, p_r, \pi^r, \epsilon^c, M - CV) \tag{3-14}$$

The term CV is the Hicks compensating variation for a change in ambiguity from ϵ^r to ϵ^c.

If the consumer maximizes utility subject to a budget constraint, he/she can also be said to minimize expenditures subject to a given level of utility. In terms of the expenditure function, the CV can be written as follows:

$$CV = e(\pi^r, \epsilon^c, u^o) - e(\pi^r, \epsilon^r, u^o) > 0 \tag{3-15}$$

If Segal's assumptions hold, and the value of a less ambiguous lottery is higher than a more ambiguous one, then the willingness to pay for a marginal reduction in ambiguity from ϵ^r to ϵ^c must be positive. Consumers should thus be willing to pay some amount above what they would pay to get risk reduction only to get ambiguity reduction. The second hypothesis of this research is:

$$- \left[\frac{\partial CV}{\partial \epsilon^c} \right]_{\epsilon^r} > 0 \tag{3-16}$$

where $\left[\frac{\partial CV}{\partial \epsilon^c} \right]_{\epsilon^r}$ indicates that the expression is evaluated at ϵ^r.

Hypothesis 2. The marginal value of a decrease in ambiguity is positive.

This hypothesis can also be developed by using equation 3-11 to solve for $-(\partial CV/\partial \epsilon^c)$. This is shown in Appendix 3-2.

The Effect of Baseline Ambiguity on WTP for Certification

Figure 3-1 shows the SOP distribution of an adverse health outcome from pesticide residues for certified and regular apples for two consumers (consumer A and consumer B). The consumers perceive the same baseline risk (π^r) and the same amount of risk reduction (π^r-π^c) when switching from the regular apples to the certified apples. However, consumer A has a higher level of initial ambiguity than consumer B. The amount of risk reduction consumer A obtains when switching from regular to certified apples is uncertain because of the large variance in the SOP distribution. The risk faced after moving to the certified apple when risks are highly ambiguous may not be significantly different from the risk associated with the regular apple. The motivation to move to certified apples is then gone. The risk reduction for consumer B, on the other

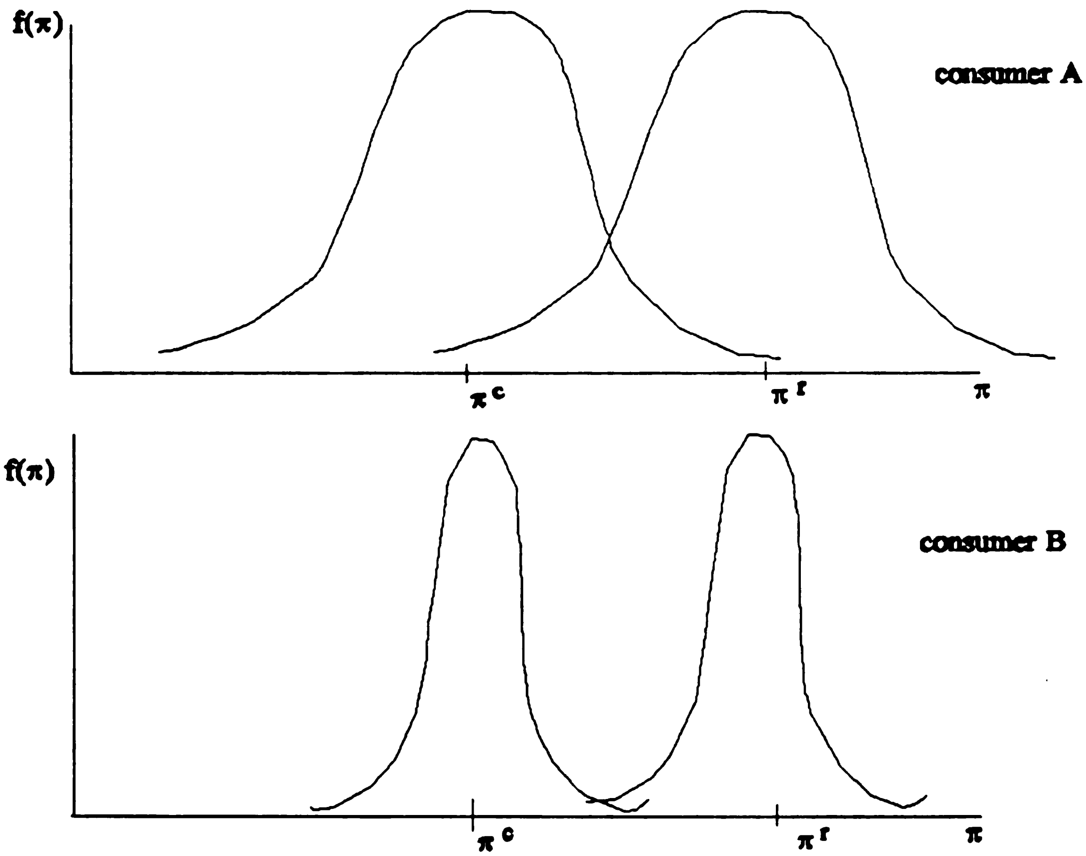

Figure 3-1: SOP for high initial ambiguity consumer (consumer A) and low initial ambiguity consumer (consumer B)

hand, is clear. Although the mean risk reduction is the same in both cases, the consumer with the high ambiguity should not be willing to pay as much for the certification as the low ambiguity consumer.[45] The following hypothesis results:

Hypothesis 3. The WTP for certification decreases with initial ambiguity, holding ambiguity reduction, baseline risk, and risk reduction constant.

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[45] This scenario assumes there is no ambiguity reduction when switching from regular to certified apples. It looks only at the effect of baseline ambiguity on WTP for certification.

This hypothesis implies that consumers who perceive higher ambiguity from the regular apple should be willing to pay **less** for certification than those people who perceive lower ambiguity, all else held constant.

The Effect of Baseline Risk on WTP for Certification

Jones-Lee (1974) shows that the marginal value of risk reduction increases with initial (or baseline) risk, π^r. He determines this by differentiating the expression for the marginal value of a change in risk with respect to initial risk level. The finding in the case of ambiguous risks is that consumers who perceive higher baseline risks from the regular apple should be willing to pay **more** for certification than people who perceive lower baseline risks.[46] That is,

$$\frac{\partial\left[-\dfrac{\partial CV}{\partial \pi^c}\right]_{\pi^r}}{\partial \pi^r} > 0 \qquad (3\text{-}17)$$

Hypothesis 4. The WTP for certification **increases** with initial risk.

Assumptions

In order to use the RDEUWA model to develop the above hypotheses, it is necessary to make several assumptions. This section outlines the assumptions used.

This research assumes that there are only two possible states of the world: an adverse health outcome **does** result from pesticide residues, and an adverse health

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[46] This calculation is shown in Appendix 3-3.

outcome **does not** result from pesticide residues.[47] The utility and indirect utility associated with no adverse health outcome are normalized to 0, i.e., $u_{nh}(\cdot)=0$ and $v_{nh}(\cdot)=0$.[48] If the health effects from pesticide residues have a negative effect on utility, then utility and indirect utility in the state of the world in which one experiences an adverse health effect from pesticide residues ($u_h(\cdot)$ and $v_h(\cdot)$) are negative.

Although the restrictions outlined in Chapter 2 regarding the bounds on $\gamma^i\epsilon$ still hold, γ^i does not vary across decision makers. The parameter γ^i varies with the possible probabilities, but does **not** vary by individual. The scale of γ^i is such that whatever the scale of ϵ, $\gamma^i\epsilon$ will be between 0 and 1. The term ϵ, then, is not restricted to lie between any bounds.

The approach here also assumes that q^j, the probability that the j^{th} probability is the actual probability, is the same for all decision makers.

People may take actions (averting behavior) to affect the probability of experiencing a health problem someday because of pesticide residues in food. They may wash or peel their fruit and vegetables before eating them, for example.[49] These actions may be complements or substitutes to acquiring the certification, i.e., people

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[47] Pesticide residues may result in several types of health outcomes with different degrees of severity. However, to keep the analysis simple, we consider only two health outcomes (none and any). The model can be modified to accommodate several (or continuous) health outcomes.

[48] $u_{nh}()$ is utility in the state of the world in which no adverse health outcome from pesticide residues results and $v_{nh}()$ is the indirect utility in the same state. $u_h()$ is utility in the state of the world in which an adverse health outcome from pesticide residues occurs and $v_h()$ is the indirect utility in the same state.

[49] There are several other actions people might take. They might grow their own produce, or buy organic produce.

may continue to take the actions they usually do (actions and certification are then complements) or they may discontinue taking those actions because they perceive the certified apple offers the reduction in risk they were achieving by their actions (actions and certification are substitutes).[50] The questions developed in the survey about the risks from pesticide residues are all framed in terms of pre-averting behavior. The probabilities obtained from the survey are thus all pre-averting behavior.

Measuring Willingness to Pay for Certification

Freeman (1993) shows that the CV for a change in the price of a good is equal to the area to the left of the Hicks-compensated demand curve between the initial and new prices. In this research, when a consumer switches from the regular apples to the certified apples he/she moves from a situation in which the price of the certified apples is prohibitively high (or, if the certified apples are not available, the price of certified apples is effectively infinite) to a situation in which the price of the certified apples is such that consumption of certified apples is positive. The CV for the certification is then the area to the left of the Hicks-compensated demand curve (h^c) between the price at which demand for certified apples is zero (the "choke" price) and the price at which the certified apples are offered. This is a measure of the surplus from the certified

[50] This research does not develop hypotheses about the relationship between risk reduction acquired through consumers' own actions and risk reduction acquired through buying certified rather than regular apples (i.e., it does not develop hypotheses about whether these actions are substitutes or complements). It does, however, measure empirically the relationship between the two. This is discussed further in Chapter 5.

apples that is due strictly to the presence of the certification indicating the pesticide residue level. This is shown graphically in Figure 3-2.

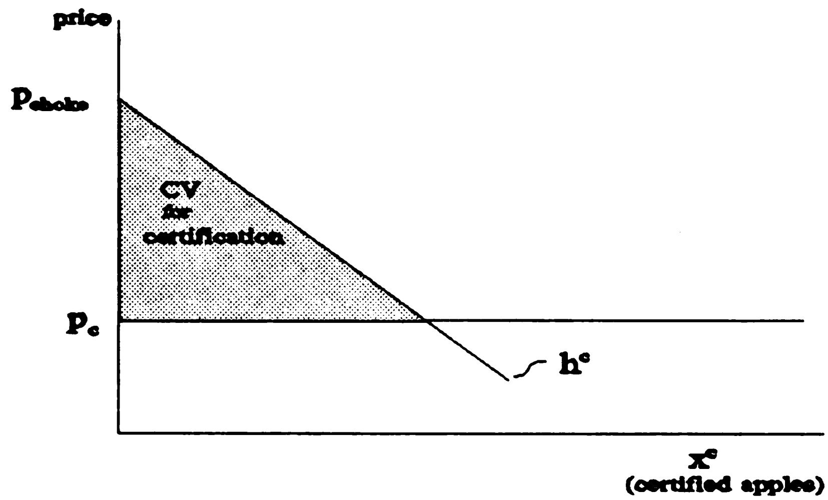

Figure 3-2: CV for Certification on Apples

When a consumer chooses the regular apple at a market price, he/she also receives some surplus; this surplus is due to the "appleness" of the regular apple that is worth something to the consumer above the market price. Since the regular and certified apples are identical except for their price and certification, when the consumer chooses the certified apple, he/she could have consumed the regular apple and still gotten the "appleness." The surplus associated with the certified apple is thus due **only** to the certification and not due to its "appleness."

The CV can also be written in terms of the expenditure function, i.e., it is the difference in the expenditure required to keep the individual at the initial level of utility, u^{o}, when the price changes from p_c^2 to p_c^1. Thus:

$$CV = e(p_c^2, \pi^c, \epsilon^c, u^o) - e(p_c^1, \pi^c, \epsilon^c, u^o) \tag{3-18}$$

where p_c^1 is the price of certified apples when the consumer chooses regular apples (i.e., p_c^1 is the "choke" price or the price at which the demand for certified apples is zero), and p_c^2 is the market price of certified apples at which there is positive demand for the certified apples.

Since CV is defined as the difference between two levels of expenditure at two different prices, it can also be written as (Freeman 1993):

$$\int_{p_c^2}^{p_c^1} \frac{\partial e(p_c, \pi^c, \epsilon^c, u^o)}{\partial p^c} dp_c = \int_{p_c^2}^{p_c^1} h^c(p_c, \pi^c, \epsilon^c, u^o)\, dp_c \tag{3-19}$$

This measure of the welfare associated with the certified apple is inconvenient because the Hicks-compensated demand curve upon which the true CV is based is unobservable. While the ordinary demand curve upon which the Marshallian consumer surplus is based is observable, the Marshallian consumer surplus is flawed as a welfare measure as it assumes constant marginal utility of income. The question then is can we use the Marshallian consumer surplus as close approximation to the true welfare measure? Willig (1976) found that the differences between the Marshallian measure and other welfare measures, such as the CV, are likely to be small. He says "the error will often be overshadowed by the errors involved in estimating the demand curve" (Willig 1976, 589). Freeman (1993, 61) also states that "the differences among the measures appear to be small and almost trivial for most realistic cases."

Several methods have been developed for estimating exact welfare measures using either a Taylor's series expansion of the indirect utility function based on terms that are derivatives of the ordinary demand functions, or by specifying a flexible functional form for the indirect or direct utility function (Reaume 1973; McKenzie and Pearce 1976, 1982; Mckenzie 1976, 1983).[51] Freeman points out that the Taylor's series expansion approach "has been criticized as being cumbersome...potentially inexact because successive terms of a convergent Taylor's series are not necessarily monotonically decreasing...and unnecessary" (Freeman 1993, 67).

Because the issue of the appropriate approach to measuring welfare has not been resolved in the literature, this research uses the consumer surplus based on the ordinary demand curve as a measure of the welfare associated with the certified apple.

The next chapter describes the survey used in this research to test the hypotheses developed in this chapter. Chapter 5 presents the econometric techniques used to test the hypotheses and presents both descriptive and analytical results.

[51] These approaches are reviewed in Freeman (1993).

CHAPTER 4: SURVEY DESIGN AND DATA COLLECTION

Use of Contingent Valuation Survey Methods to Value Non-Market Goods[52]

This chapter describes the design of the contingent valuation survey (CVM) used to test the hypotheses developed in chapter 3. The first section describes the design of the CVM survey used in this research. It then presents the methods for measuring both risk and ambiguity. The third section describes how the CVM survey was implemented. The concluding section uses Carson's (1991) validity criteria to evaluate the major strengths and weaknesses of the research design.

Design of CVM Survey

Contingent valuation survey methods (CVM) offer a technique for eliciting the value consumers' attribute to non-market goods or to characteristics of goods. In contingent-valuation surveys, respondents are asked questions about hypothetical scenarios; the value they place on the non-market good or characteristic can then be determined. Respondents may be asked to directly state their willingness to pay for the non-market good, or they may be asked about the purchase decisions they would make at various prices and about their perceptions of the characteristics (such as pesticide residue levels) of the good.[53,54] In the latter case, the data can be used estimate the

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[52] The rest of this chapter draws heavily from van Ravenswaay and Wohl (1993) and from van Ravenswaay, et al (1992).

[53] This later approach is technically called "contingent behavior" rather than "contingent valuation" (Freeman 1993).

demand for the good as a function of the non-market characteristics of the good. Shifts in the demand due to changes in the product attributes are then used to estimate the willingness to pay for changes in the attributes.

This research uses a contingent valuation survey (presented in Appendix 5-1) to measure consumers' purchase decisions under alternative policy scenarios. It also elicits consumers' risk and ambiguity perceptions. The results of the survey are used to estimate the value to consumers of two pesticide residue policies that reduce risk and/or ambiguity. The first policy (Policy I) maintains the current federal standard for pesticide residues on food, but permits product claims to be made that the federal standard is met. This policy may not change the **actual** risks that consumers face from pesticide residues (if the apples already met federal standards), but it may change peoples' **perceptions** of both the risks they face and the uncertainty or ambiguity about those risks. The second policy (Policy II) permits certification that products have been produced without pesticides. This policy reduces risks to consumers and may also change peoples' perceptions about the risk and ambiguity from pesticide residues. In both scenarios, the policy may reduce the ambiguity about risks from pesticide residues by simply providing information about the levels of pesticide residues in apples.

The constructed market for apples under these two policy scenarios was presented to consumers using a contingent valuation survey instead of an experimental setting in which participants are offered actual products. This approach permits the use

[54] The pesticide residue level on apples is considered a "characteristic" of apples; risk and ambiguity are based on consumers' perceptions of residue levels, but are not themselves characteristics of the good.

of a large and representative sample at lower cost than the equivalent experimental setting.

The contingent valuation survey used in this research had several goals that influenced its design. One goal was to create a hypothetical shopping scenario for respondents that would prompt them to reveal their apple-purchasing behavior given certain prices of apples and levels of pesticide residues. Another goal was to elicit respondents' perceptions of the risks they face from pesticide residues and how those risks change with residue levels. A final goal was to examine peoples' uncertainty about risks to test whether ambiguity is a factor in determining willingness to pay for pesticide residue reduction.

The Shopping Scenario

The survey created a realistic shopping scenario by asking people to imagine that they were shopping in the fall and planning to buy some apples.[55] This guaranteed that all respondents were thinking about the same shopping scenario.

The survey did not ask people to directly state their willingness to pay for reduced pesticide residues or reduced risks since this is not a situation they are ever likely to face. Instead, it asked them about their apple-purchasing behavior under various scenarios. These are decisions people actually face when they buy apples; the responses are thus more likely to reflect real decision behavior.

[55] Respondents were first asked if their household had bought any fresh apples in the past year. The hypothetical shopping scenario was presented only to the ninety two percent of respondents who indicated they had.

Previous Survey

The questionnaire used in this study built upon the questionnaire developed by van Ravenswaay and Hoehn (1991) to estimate consumer willingness to pay for reduced risks from pesticide residues in apples. Since it used many of the same questions developed by van Ravenswaay and Hoehn, this section briefly describes the development of their questionnaire.[56]

The questionnaire used in the van Ravenswaay and Hoehn study asked respondents about their current purchases of apples, their purchase intentions for regular apples at specified prices, and their purchase intentions for apples that were said to be certified to have "no pesticide residues," "no detectable pesticide residues," and finally "no pesticide residues above federal limits." Respondents were given a range of different prices and asked how many apples they would buy if they were planning to buy apples on a typical shopping occasion in the fall. The season was specified so that all respondents would be considering similar supply conditions.

Modifications to Previous Survey

In the present research several modifications were made to the van Ravenswaay and Hoehn (1991) survey. First, this survey was conducted by telephone rather than by mail. Since van Ravenswaay and Hoehn were interested in studying the levels of pest damage that consumers would accept, their survey required that respondents react to photographs of apples with pest damage; a mail survey was thus necessary. In the

[56] For more details of the van Ravenswaay and Hoehn survey, see either van Ravenswaay and Hoehn (1991) or van Ravenswaay and Wohl (1993).

present research, however, no variations in visual aspects of apples were necessary; a phone survey was thus suitable.

A telephone survey offers several advantages over mail surveys. It allows the use of Random Digit Dialing (RDD), which generates more representative samples, it reduces non-response bias since interviewers are able to clarify questions and prompt respondents for further information, complicated skip patterns can be easily incorporated into the questionnaire design, and, since the telephone survey is computerized, data are entered directly into the computer as respondents answer questions, thus minimizing processing errors.

Substitution Possibilities

As in the van Ravenswaay and Hoehn (1991) questionnaire, the purchase intention questions in our survey were developed to reveal the **quantity** of apples respondents would likely buy at different prices during a typical grocery shopping occasion in the fall. However, in this survey respondents were given a **choice** between certified and uncertified apples, whereas in the van Ravenswaay and Hoehn (1991) questionnaire, apples were either all certified or all uncertified. Our modification allowed the substitution between different "brands" to be explicitly accounted for. In the van Ravenswaay and Hoehn (1991) questionnaire, the consumer could substitute another fruit for apples, but the price and type of that fruit were unknown. The survey used here assumed that the closest substitute to an uncertified apple was an apple certified for the level of pesticide residues. It therefore offered respondents both products and specified their prices (prices varied across households). As in the van

Ravenswaay and Hoehn (1991) survey, respondents were told to assume that all fruits other than apples were not certified for pesticide residue levels. The two studies represent two different policy alternatives. The van Ravenswaay and Hoehn (1991) study sought to evaluate a change in residue standards; the present study evaluates residue-labeling policies.

Content of Certification

The certification on the apples was also changed. The survey omitted the "no detectable residues" certification since van Ravenswaay and Hoehn (1991) found it was statistically indistinguishable from the certification "meets federal standards for pesticide residues." The certification "no pesticide residues" was changed to "produced without pesticides" since it is technically impossible to guarantee "no pesticide residues" when pesticides may be airborne, waterborne, or soilborne at the farm where they were grown, the warehouse where they were stored, or the store where they are sold.

In order to make the questions shorter and more tractable, half the sample was asked to make a choice between regular apples (no certification) and apples with the certification "produced without pesticides;" the other half was asked to choose between regular apples and apples with the certification "no pesticide residues above federal limits." The type of certification was randomly assigned to respondents based on the last digit of the respondents' phone number.

Measuring Risk Perceptions

Objective Versus Subjective Risk Estimates

In order to test the hypotheses developed in chapter 3, the study estimates the demand for certified apples as a function of both risk and ambiguity. Market data does not allow this, however, as it is difficult to know the levels of pesticide residues present in the apples people buy; and it is difficult to know peoples' **perceptions** of the levels of pesticides present in the apples they buy. Some researchers have applied "objective" or "scientific" estimates of the risks from pesticide residues to data on the demand for organic products to assess consumers' willingness to pay for reduced residues and reduced risks (Hammitt 1986). However, focus groups with consumers conducted by van Ravenswaay and Hoehn (1991) found that organic labels on produce were not interpreted in a consistent fashion by consumers. Consumers buy organic products for several reasons, only one of which is the reduced pesticide residues they offer. For example, some consumers believe organic products have higher nutrient value and are more tasty than conventional products. Furthermore, both the risks and ambiguity about risks from pesticide residues are "subjective," i.e., individuals vary in their perceptions of the risks they face from the same product. When subjective estimates of risk diverge significantly from the "objective" or "scientific" estimates (Kahneman and Tversky 1979, Eom 1994), assuming that all consumers use the "objective" estimate of the risks when making purchase decisions distorts the true willingness to pay for risk reduction. Since consumers make decisions based on their **own** assessments of the riskiness of products, and **not** on scientists' estimates (of which they are generally not aware), it is important to understand peoples' subjective risk estimates.

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Improvements in Risk Perception Questions

To develop measures of both baseline risk and changes in risks, several improvements were made to the van Ravenswaay and Hoehn (1991) methods of eliciting risk perceptions. The van Ravenswaay and Hoehn (1991) study found that there was considerable variation across households in the actions households undertook to avoid pesticide residues. One third of their sample reported that they washed fresh produce with soap and water, bought organic produce, or grew their own produce in order to reduce or avoid pesticide residues in food. To ensure that each household was comparing certified apples to uncertified apples rather than to apples that might have reduced pesticide residues because of one's own actions, the survey asked respondents to estimate the risks from pesticide residues to a person from a household like theirs who did **nothing at all** to avoid or reduce pesticide residues in food.

Another improvement in the risk perception questions was the increased specificity in the meaning of quantitative risk. In the van Ravenswaay and Hoehn (1991) survey, respondents were asked what the chances were that someone from **their** household would have a health problem someday because of pesticide residues in food. To ensure that respondents to the present survey were considering the risk to a person in the whole population, the survey asked respondents in this survey to imagine that there were a million people from households **like theirs** who did nothing at all to reduce or avoid pesticide residues in food. It then asked them what they thought the chances were that a person from one of these households would have a health problem someday because of pesticide residues in food. To help ensure the respondents were estimating population risks, the response categories used in the van Ravenswaay and Hoehn (1991) survey were modified to specify numbers of people out of one million who would be expected to have a health problem someday because of pesticide residues in food. They could choose from the response categories: one in a million, one in 100,000, one in 10,000, one in 1,000, one in 100, one in 10, one in 5, one in 2, certain to happen. Responses to this question measure perceptions of **baseline** risk.

A third improvement to the risk perception questions was that respondents were asked for a **qualitative** statement of the risks from pesticide residues before being asked for a **quantitative** estimate. Respondents were asked whether they would say there is "no chance," "it is very unlikely," "somewhat unlikely," "somewhat likely," "very likely," or "certain to happen" that someone from a household like theirs would have a health problem someday because of pesticide residues in food. The interviewer used this qualitative answer to prompt the respondent for a quantitative estimate of risks. This approach permits an examination of the correlation between a qualitative, but more easily understood estimate, and a quantitative, but more precise estimate. In fact, the two measures are highly correlated.

To measure perceptions about **changes** in risk, the survey also asked respondents how much (in percentage terms) their risks would be reduced if the federal government tested and certified that the apples met federal standards for pesticide residues (or, for half the sample, that apples had been produced without pesticides). This information is used to calculate the perceived risks associated with the certified apples.

The risk perception questions were all in terms of the chance of a health problem someday because of pesticide residues in **food**. The responses thus represent respondents' perceptions of the risks from pesticide residues in **all foods**, not only the risks from residues in apples. Pretests done for the van Ravenswaay and Hoehn study (1991) revealed that this was the easiest way for people to communicate their perceptions of the risks from pesticide residues; expecting people to accurately assess the risks due specifically to pesticide residues on apples is unrealistic. The questionnaire was thus designed to facilitate eliciting accurate measures of peoples' risk perceptions.

The quantitative measures of the perceptions of risk from all foods (both baseline and changes) are included as an explanatory variables in the estimated demand model in the form obtained from the survey, i.e., as **lifetime** risks from **all** foods.[57] This is appropriate if one assumes that the risks from apples are a constant proportion of the risks from all sources (van Ravenswaay and Hoehn 1991). However, when using the model for sensitivity analysis to see how a marginal change in risks affects willingness to pay for certification, we adjust the willingness to pay for certification to calculate annual willingness to pay a change in **annual** risk.

Measuring Ambiguity Perception

The conceptual framework developed in chapter 3 shows that ambiguity, defined as the "spread" of the second-order probability distribution, is theoretically an important determinant of the willingness to pay for residue certification. The problem arises as to how to measure ambiguity without knowing the shape of the respondents' second-order probability distribution. Since ambiguity perceptions cannot be directly measured,

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[57] The Heckman two-stage model that is used to estimate the demand for certified apples is described in detail in Chapter 5.

several proxies were developed to reveal respondents' underlying perceptions of the spread of their second-order probability distribution. First, respondents were asked how "sure" they were about both their qualitative and their quantitative risk estimates. A Likert scale (1=very sure, 2=somewhat sure, 3=somewhat unsure, 4=very unsure) was used to measure sureness in risk estimates. This study assumes that the less "sure" someone is, the wider is his/her second-order probability distribution. One of the problems with this measure is that it assumes that the ordinal "sureness" scale employed in the survey is interpreted similarly by all respondents.

There are several factors that may influence someone's level of ambiguity about the probability of a health problem resulting from pesticide residues in food. They include the level of trust that the government is setting appropriate standards, the level of trust that once these standards are set, they are being met, and the level of trust that the scientific community understands the risks from pesticide residues and is truthful about that knowledge. These trust levels are alternative proxies for measures of ambiguity. The empirical section in chapter 5 tests whether they have any effect on the demand for certified apples.

The proxies just described for ambiguity are all proxies for **baseline** ambiguity. They are related to the ambiguity associated with the regular apples. This allows us to gauge differences in ambiguity across people. Although the survey did not ask respondents about their perceptions of the changes in ambiguity when switching to the certified apples, this research develops a proxy for the **change** in ambiguity across certification type. People who do not currently trust that the standard for pesticide residues is being met, **and** who feel that if the government tested and certified apples for their residue level that such a program would be effective are likely to experience the most ambiguity reduction when switching to the certified apples. A dummy variable in the demand model tests the effect of reducing ambiguity on the demand for certified apples.

Other Issues

Prices

Respondents were told the prices of both regular and certified apples. Each respondent received one of forty price combinations of regular and certified apples ranging from $0.49 to $1.19 for the uncertified apple and $0.49 to $1.59 for the certified apples. To ensure randomization of the price combinations given to respondents, price combinations were assigned on the basis of the last four digits of the respondents' phone number. Respondents were told that all apples would look the same as those they usually buy. They were then asked if they would buy all of one type of apple (certified or uncertified), some of both, or none at all, and the quantities of those apples they would likely buy at the given prices.

The contingent valuation survey used in this research was an "experiment" in which the prices of regular and certified apples were systematically varied to ensure price variation in the data. The survey thus generates respondents' purchase intentions for apples on a typical shopping occasion. However, the estimation of the surplus associated with the purchase of certified apples is based on specific prices for both regular and certified apples that are the same for all consumers. The price of the regular apple is the average retail price (per pound) of red delicious apples in Michigan in June/July, 1992 (the time period of the survey) of $0.98 per pound (United States Department of Agriculture 1993).

Apples certified exactly as they were described in the survey are not currently available on the market. In order to estimate the cost per pound of certifying apples to have been produced without pesticides (or to meet federal standards for pesticide residues) this study used cost data from Nutriclean, a private organization located in California that certifies produce for pesticide levels.[58,59] This calculation produced an estimate of $0.06 per pound. The price of the certified apples was thus $1.04 ($0.06 higher than the regular apple price).

Implementation of the CVM Survey

The target population for this study was Michigan households that purchase food. A sampling error of ± 1% required 1000 completed surveys. To reach this goal, we purchased a sample of approximately 2600 Michigan telephone numbers from Survey Sampling Incorporated (SSI). The sample purchased from SSI was drawn using random digit dialing. Of these, only 1730 phone numbers had to be used to reach the goal of 1000 completed interviews. Of the eligible households contacted, 67% (1003)

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[58] The cost to the government of certifying apples would most likely be different from that of a private firm. However, the cost to Nutriclean gives us a "ballpark" figure.

[59] Nutriclean's cost per sample to certify apples (regardless of the size of the operation) is approximately $1200 (Jim Knundson, Nutriclean, telephone communication, September, 1994). We use this data and the 1987 Michigan Census Data on total pounds of apples harvested and number of farms harvesting to calculate the price per pound of certification.

completed the survey. The telephone interviews were conducted by the Institute for Public Policy and Social Research (IPPSR) at Michigan State University.

The surveys were conducted with adults over the age of 18 who did most of the food shopping for their household. They were conducted by telephone during June and July, 1992. Each survey averaged 16 minutes in length but varied from 7 to 35 minutes.

All questions that were added to or revised in the van Ravenswaay and Hoehn (1991) questionnaire were pretested using face-to-face interviews with typical household food purchasers. Further pretests of the entire questionnaire were also done in conjunction with IPPSR using telephone interviews with Michigan consumers. The pretest interviews, as well as the final interviews, were conducted by IPPSR personnel who were specially trained to administer the survey. The pretests improved not only the survey instrument, but also allowed us to develop detailed instructions on how interviewers should handle unusual or difficult situations, thus improving the reliability of data collection.

The CATI software used by IPPSR to conduct the telephone survey allowed for skip patterns that depended on how respondents answered certain questions. Interviewers were thus able to tailor each survey to the particular responses of the individual being surveyed.

A Critique of Survey Methods

The results from contingent valuation surveys are often criticized because of the large divergence between what people say they will do, and what they **actually** do.

Carson (1991) has developed a series of criteria for designing constructed markets to increase the reliability of the results. His criteria focus on the theoretical accuracy and policy relevance of the scenario offered in the survey, as well as on the extent to which the scenario is understandable, plausible, and meaningful to respondents. This section uses these criteria to evaluate the strengths and weaknesses of the contingent valuation survey design used in this study.

To guarantee theoretical accuracy, the researcher must ensure that features of the created scenario are compatible with economic theory. For example, property rights must be clearly specified, the respondent's budget constraint must be binding, substitution possibilities must be clearly indicated, and the payment mechanism for the good in question should result in accurate estimates of value.

The theoretical framework outlined in chapter 3 warrants the use of a private-goods market. Individual demand curves for the basis of the measure of consumers' willingness to pay for marginal changes in risk and ambiguity. The private market for apples is thus an appropriate setting for measuring willingness to pay for risk reduction.

The budget constraint of the respondent is likely to be binding since respondents were given the prices of goods in a market setting. It is doubtful that respondents would strategically exaggerate the number of apples they would buy at these prices. It is also unlikely that people would have difficulties making decisions about products. Most people buy apples; it is easy for them to accurately predict their purchasing behavior.

It is important in survey design to incorporate substitutes for the good in question. Otherwise, people are responding to questions out of the context in which they would actually be required to make payments. The constructed market used in this research consisted of both certified and uncertified apples, with the prices for both indicated. Since certified apples are probably the closest substitute for regular apples (assuming the prices for regular and certified apples are not too divergent), this approach contributes to the creation of a realistic buying scenario.

The questionnaire was designed to isolate the effects of perceived risk and perceived ambiguity on the demand for apples. The shopping scenario was structured so that respondents would assume that product attributes other than these did not vary. This was accomplished by asking respondents to consider the variety of apples they normally bought and to assume that the quality of all apples was the same as they normally observed in the fall.

It is important that the results of the survey be relevant to policy makers. Understanding the relationship between willingness to pay for pesticide residue certification and for marginal changes in risks and ambiguity can aid policy makers in designing policies regarding pesticide residues that target the concerns of consumers making decisions in the face of risks. This study considers not only how consumers value changes in the risks and ambiguity from pesticide residues, but also the effect of food labeling on consumer choice. These are all of interest to decision makers in the area of food-safety policy. The methods used to elicit perceptions about risks from pesticide residues and ambiguity about those risks can be used in any application that requires an understanding of consumers' decision making under uncertainty.

One could question the policy relevance of a scenario that considers a market where apples are the only product tested and certified for residue levels. If policy makers were to require apples to be tested and certified, they would likely also require that other produce be tested and certified. However, respondents are not likely to be able to accurately predict and describe their behavior in the more general scenario where **all** foods are described as being tested for pesticide residues. This scenario would require changing the prices of all substitutes for apples; creating an easily understandable scenario then becomes infeasible.

As the name implies, the results of contingent valuation studies are contingent upon the scenario presented to respondents. The highly specific scenario given to respondents in this survey makes it difficult to generalize the results. However, from the point of view of economic theory and respondent comprehension, the specific scenario offers the advantage of yielding results more valid than those obtained from less specific scenarios.

Respondents will be more able and motivated to accurately predict their behavior if the scenario presented to them is understandable, plausible, and meaningful. Although contingent valuation surveys commonly ask respondents to directly state their willingness to pay for specific goods or services, this research did not use this approach. Instead, it asks respondents how many apples they would likely buy under different scenarios. The demand analysis then uses this information to estimate willingness to pay for risk reduction. Since consumers are more likely to have to make market choices than to be asked to pay directly for reduced risks, the market scenario is more understandable, plausible, and meaningful respondents. Furthermore, consumers are typically price takers in apple markets.

Apples provide a good vehicle for studying the effects of risk and ambiguity on WTP because most households purchase apples, apples have been associated with pesticide residues in the media, and they allow people to predict their behavior under very familiar and likely circumstances.

One of the goals of this research was to develop reliable methods of soliciting perceptions of baseline risk and ambiguity as well as the perceptions of changes in risk associated with certified apples. Extensive pretesting of the survey instrument was therefore conducted to ensure that questions were thoroughly understood. Cross tabulations between qualitative and quantitative responses to risk questions suggest that respondents did, in fact, understand the nature of the quantitative risk assessments they were asked to make. Careful consideration was also given to the order of questions. The survey was designed to first get respondents thinking about their current apple purchasing behavior before asking them to make hypothetical purchasing decisions.

Many studies involving decisions under risk present respondents with scientific or objective risks and then assume that respondents use those estimates in their decision calculus. In some cases, this approach may be useful, but the presentation of the objective risks should be coupled with questions that examine how such information alters risk perceptions. Researchers cannot assume that respondents accept objective estimates of risk without consideration of their own experience and other information. The survey used in this research asks respondents to make their own assessment of the risks involved in pesticide residue consumption. This is a more realistic scenario since consumers are generally forced to make risk assessments before making purchase decisions. Furthermore, scientific or objective risk assessments are not generally available to consumers. To ensure that respondents understood the questions, risk perception questions were worded to allow respondents to think in terms of numbers of people affected rather than just in probabilities.

The survey used in this research also allows examination of baseline ambiguity about risk. Questions were asked about how "sure" respondents felt about their risk estimates and how much they trusted the government and the scientific community. Because there is a lot of uncertainty about the risks from pesticide residues, ambiguity may be an important factor in explaining consumers' willingness to pay for risk reduction. Allowing respondents to express their uncertainty about the health risks from pesticide residues may improve the validity of the risk perception measures. When respondents are given the opportunity to express their reservations, they feel less pressure to be "right," and are then more likely to give their best estimate of the risk instead of giving worst- or best-case estimates.

CHAPTER 5: ECONOMETRIC TECHNIQUES AND EMPIRICAL ANALYSIS

This chapter presents the results the CVM survey of Michigan consumers' apple-purchasing behavior and attitudes about pesticide residues in food. The chapter first presents some descriptive information from the CVM survey to provide a broad overview of the structure and content of the data. It then summarizes the general methods used to estimate the willingness to pay for pesticide residue certification based on the demand for certified apples. This is followed by a discussion of the Heckman two-stage demand model used to estimate the demand for certified apples. After defining the variables used in the estimation, the results of the first-stage PROBIT analysis and the second-stage demand estimation are presented. This is followed by a discussion of how the estimated coefficients are used to calculate the consumer surplus associated with the certified apples and to conduct the sensitivity analyses. The chapter then presents the results and discusses their implications.

General Survey Results

The tables in this section present some descriptive results from the CVM survey used in this research. These results help assess how representative the data are of the Michigan population. The data are presented in the following categories: demographics, risk perceptions, perceptions of ambiguity, perceived risk reduction when foods are certified, perceived health effects from pesticide residues in food, attitudes toward government and the scientific community, and purchase intentions.

Demographics

To assess how representative of the Michigan population the sample used in this study is, the results from the present survey are compared to the data from the 1990 Michigan Census or the "Current Population Reports." The census data and the data from the "Current Population Reports" are based on the population of Michigan when possible, the US when not.

Table 5-1 shows that the average household in this study is about the same size as the average household in Michigan in 1990. However, the current sample overrepresents households with children under the age of 18 and underrepresents single-person households.

Table 5-2 indicates that this sample may underrepresent low-income households and overrepresent wealthy households. However, the mean before-tax household income is comparable to the Michigan average.

Table 5-3 shows age of respondents. Elderly people (over 75) and very young people (under 25) may not be adequately represented in our survey.

Table 5-1: Household Demographics

Characteristic	This study N = 1,003	1990 Census (Michigan)
Average household size (# of persons)	3.0	2.7
Percent of households with children under 18	54.8 %	49.2 %
Percent of single-person households	13.3 %	23.6 %

* Figures may not add to 100% due to rounding

Table 5-2: Household Income

Income	This study N=1,003	1990 Census[1] (US)
Less than $10,000	3.7%	14.9%
$10,000 - 49,999	58.7%	60.4%
$50,000 or more	28.2%	24.6%
No answer / don't know	9.6%	NA
Mean before-tax household income	$41,025	$37,403

1. from Current Population Reports. Series P-60, No. 174. 1990.
* Figures may not add to 100% due to rounding

Table 5-3: Age of Respondent

Age of Respondent	1990 Census (Michigan)[1]	This Study	Age of Respondent
18-24	14.7%	8.1%	25 or younger
25-44	43.6%	22.2%	26-35
		23.6%	36-45
45-54	13.9%	17.1%	46-55
55-64	11.6%	13.8%	56-65
65-74	9.6%	9.9%	66-75
75+	6.6%	4.9%	76+
		0.4%	No Answer

* right-hand age categories apply to this study; left-hand age categories apply to census data.

1. percentages apply to population over 18 years of age.

The demographic results indicate that this survey probably represents the Michigan population well. It is probably safe to use the results of our survey to extrapolate to the Michigan population as a whole.

Risk Perceptions

The perceived baseline risk level from pesticide residues in food is presented in Table 5-4. The average perceived risk is between 1 in 10,000 and 1 in 1000. This is the same mean perceived risk found by van Ravenswaay and Hoehn (1991), although the wording of the questions differs between the two surveys. However, many fewer households in our study perceived no chance or a chance of 1 in a million. This result

Table 5-4: Perceived Chance of a Health Problem

"Suppose there were a million people from households like yours who did nothing to reduce or avoid pesticide residues in food. What do you think the chances are that a person from one of these households would have a health problem someday because of pesticide residues in food?"

Response (prompted)	Percent Respondents
No chance	2.4%
1 in a million	4.1%
1 in 100,000	14.1%
1 in 10,000	23.0%
1 in 1,000	22.8%
1 in 100	10.8%
1 in 10	8.4%
Certain to happen	8.2%
Don't know/no opinion /refused to answer	6.3%

Note: N = 1,003. Figures may not add to 100% due to rounding

was expected because the earlier survey did not control for the possibility that consumers may have been taking their own actions (such as washing or peeling fruits and vegetables) to reduce or avoid pesticide residues in food.

These results show that perceptions of the baseline risks from pesticide residues in food vary significantly across people. Consequently, surveys that assume that risk perceptions among all consumers are the same would lead to incorrect estimates of willingness to pay for risk reduction.

Perceived Risk Reduction when Foods are Certified

The risk levels presented in Table 5-4 are the perceived risks associated with the consumption of conventionally produced foods. If foods are certified for different levels of pesticide residues, many people will perceive that those risks change. Table 5-5 shows the percentage risk reduction respondents felt they would be getting if foods were certified by the government as indicated.[60] Respondents felt they got more risk reduction when foods are "produced without pesticides" than when foods "meet federal standards." However, the difference in risk reduction between the two types of certification is not large, suggesting that consumers may perceive that either the current federal standards adequately protect them from the risks of pesticide residues, or that they do not distinguish the exact content of the certification when making their assessments of risk reduction.

Perceptions of Ambiguity

In addition to the questions about baseline risks and the changes in risks from pesticide residues in food, Michigan respondents were also asked to indicate their level of sureness about risk. More specifically, they were asked "how sure are you that the chance of a health problem is _____? (blank filled in with respondent's estimate)." The answer to this question is used as a proxy for ambiguity. Despite the difficult nature of quantitatively assessing risks, Table 5-6 shows that 23% of respondents were very sure about their risk estimates, 45% were somewhat sure, 20% were somewhat unsure, and

[60] The perceived risk levels associated with the labels can be calculated by applying the perceived risk reduction with the labels to the risk levels in Table 5-5.

Table 5-5: Perceived Reduction in the Risks from Pesticide Residues When Foods Meet Federal Standards for Pesticide Residues or Are Produced Without Pesticides

"Now suppose that all foods met the federal standard for pesticide residues (split sample received: Now suppose that pesticides were not used in producing foods). What percent do you think that would reduce the chances of a health problem happening someday to people who currently do nothing to reduce or avoid pesticide residue?" (open-ended)

	Certification: "Meets federal standards" N = 434	**Certification: "Produced Without Pesticides"** N = 418
Percent Reduction	**Percent Respondents**	
0%	0.9%	1.7%
0% to 20%	10.6%	13.4%
20% to 40%	14.3%	7.2%
40% to 60%	28.1%	29.9%
60% to 80%	21.9%	19.4%
80% to 99%	9.4%	13.2%
100%	4.1%	15.3%
Refused / no answer	10.6%	0.0%

Note: N=852. Respondents who answered "there was no chance of a health problem," or who answered "don't know/no opinion/refused" to the question in Table 5-4 were not asked this question. Figures may not add to 100% due to rounding.

Table 5-6: Sureness about Health Risk

"How sure are you that the chance of a health problem is ______? (blank filled in with respondent's estimate)"

Response (prompted)	Percent Respondents
Very sure	23.4%
Somewhat sure	44.7%
Somewhat unsure	19.9
Very Unsure	5.3
Don't know/no opinion	6.7

Note: N=1003. Figures may not add to 100% due to rounding.

only 5% were very unsure. The results of this question demonstrate that people have different levels of confidence in their risk estimates (i.e., the spread of the SOP varies by individual).

Attitudes Toward Government and the Scientific Community

Table 5-7 shows the results to questions about trust in the government and the scientific community. This research assumes that trust in the government in scientific community influences consumers' ambiguity levels. Almost 50% of respondents said they either "somewhat disagree" or "strongly disagree" with the statement "I trust the federal government to set the same standards that I would set in limiting the amount of pesticide residues allowed in food." Even if there were certification guaranteeing that foods met federal standards, many respondents felt that standard would not be one they would agree with. There is similarly sentiment about the federal standards for pesticide residues.

Table 5-7: Attitudes Toward the Government and the Scientific Community

Statement	Strongly agree	Somewhat agree	Somewhat disagree	Strongly disagree	Don't know/ no opinion/ refused
	Percent Respondents				
I trust the federal government to set the same standards that I would set in limiting the amount of pesticide residues allowed in food.	14.2%	37.9%	25.7%	22.0%	0.2%
I trust that once the federal standards are set, all the food I buy will meet those standards.	13.6%	38.0%	27.8%	20.0%	0.6%
The scientific community can be trusted to be truthful about what they know about health risks from pesticide residues.	12.5%	39.7%	25.4%	21.1%	1.3%
The health risks associated with current levels of pesticide residues in food are well known and understood by the scientific community.	22.0%	39.6%	23.2%	12.8%	2.4%

Note: N=1003. Figures may not add to 100% due to rounding.

those standards." These respondents also do not trust the enforcement efforts.

Of the respondents, 36% said they either somewhat disagree or strongly disagree with the statement that "the health risks associated with current levels of pesticide residues in food are well known and understood by the scientific community." Furthermore, 46% of respondents said they either somewhat disagree or strongly disagree with the statement "the scientific community can be trusted to be truthful about what they know about the health risks from pesticide residues." There is substantial lack of confidence that the scientific community has presented trustworthy information about the risks associated with pesticide residues in food.

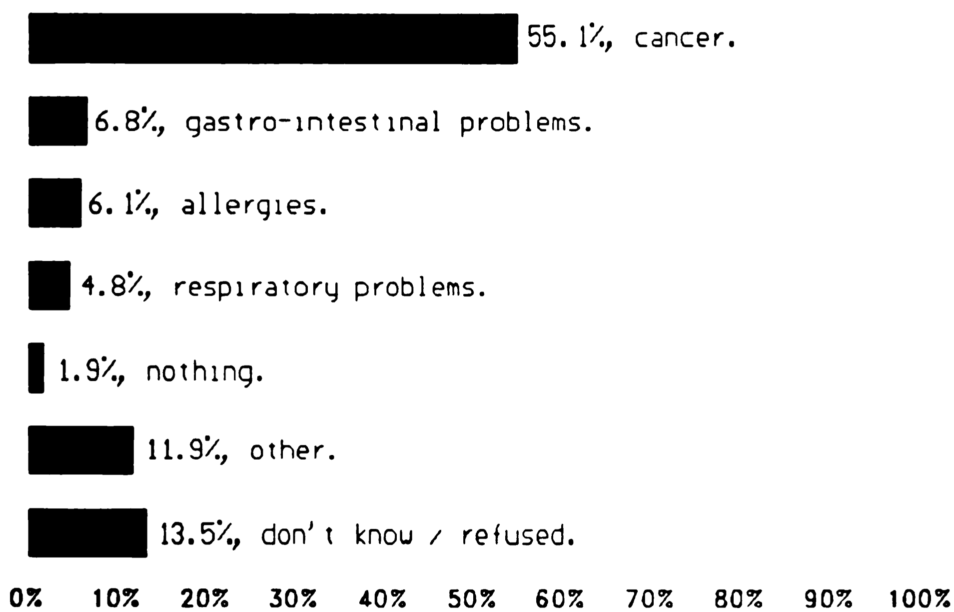
It appears that ambiguity does not stem from only one source, although it does seem that ambiguity derives less from scientific uncertainty about risks than from the trustworthiness of scientists and government regulators.

Perceived Health Effects from Pesticide Residues in Food

Table 5-8 shows the types of health effects people associate with pesticide residues in food. The survey asked respondents: "suppose someone from a household like yours had a health problem someday that resulted from the current levels of pesticide residues in food. In your opinion, what would the health problem most likely be? (open-ended)." While respondents perceive a variety of health problems associated with pesticide residues in food, more than 50% believe that cancer is the most likely illness. Although these results are difficult to compare to the results from van Ravenswaay and Hoehn because of the different wording of the question in that survey, they also found that cancer was considered the most likely health effect to occur.

Table 5-8: Perceived Health Effects Associated with Pesticide Residues in Food

"Suppose someone from a household like yours had a health problem someday that resulted from the current levels of pesticide residues in food. In your opinion, what would the health problem most likely be?" (open-ended)



Purchase Intentions

Table 5-9 shows respondents' purchase intentions for certified and uncertified apples at different prices. The table gives the percentage of respondents indicating they would buy that type of apple if both certified and uncertified apples were available. The data do **not** indicate the quantities purchased. There was not a large difference in purchase intentions between the subsample that evaluated the "meets federal standards" certification and the subsample that evaluated the "produced without pesticides" certification. This is evidence that there may be substantial value in reducing ambiguity about whether foods meet current federal standards for pesticide residues.

Table 5-9 suggests that the difference in price between certified and uncertified apples is an important factor in respondents' decision to purchase certified apples. Respondents were interested in certified apples only if the price was low enough relative to the uncertified apple. Specification of substitution possibilities is clearly important.

Willingness to Pay for Certification

As described in chapter 3, the area to the left of the ordinary demand curve for certified apples above a specified price and below the choke price approximates the willingness to pay for residue certification. This study uses the data from the survey of Michigan households to estimate the demand for certified apples.[61] The consumer surplus is calculated for each respondent; the average surplus for the sample is then calculated to obtain the average willingness to pay for certification.

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[61] The survey is described in detail in chapter 4.

Table 5-9: **Willingness to Buy Certified and Uncertified Apples**

TYPE OF APPLE	**PERCENT RESPONDENTS INDICATING WILLINGNESS TO BUY TYPE OF APPLE**			
	Certification: No Pesticide Residues Above Federal Standards		**Certification: Produced Without Pesticides**	
	PRICE DIFFERENCE: $0.20 or less	PRICE DIFFERENCE: $0.30 or more	PRICE DIFFERENCE: $0.20 or less	PRICE DIFFERENCE: $0.30 or more
Regular Apples	16.8%	30.4%	16.1%	26.7%
Certified Apples	71.1%	48.5%	68.3%	50.3%
Some of Both	8.4%	15.2%	9.1%	14.1%
None at All	3.2%	4.4%	4.8%	8.4%
Don't Know/ Refused	0.5%	1.5%	1.6%	0.5%

Note: N=1003. Figures may not add to 100% due to rounding. Numbers in table are percentages selecting type of apple at given prices, **not** how much would be purchased.

The Effect of Risk and Ambiguity on Willingness to Pay for Certification

The willingness to pay for the residue certification is estimated given the respondents' perceived levels of risk and ambiguity associated with the regular and certified apples. The marginal value of a change in risk or a change in ambiguity is calculated by using the coefficients from the demand analysis to conduct sensitivity analysis on the total willingness to pay for certification. That is, we see how the total willingness to pay for certification changes with small changes in either risk or ambiguity, holding the levels of all other variables at their original values.

Modeling the Demand for Certified Apples as a Two-Stage Process

The survey used in this research asked respondents to consider a hypothetical shopping scenario in which both regular and certified apples were available at stated prices. Respondents were first asked if they would choose regular apples, certified apples, some of both, or no apples at all. They were then asked how many apples of that particular kind they would buy.

The decision to buy the certified apples can be thought of as a two-step process. The consumer must first decide whether or not to buy the certified apples. Once the decision to buy them has been made, he/she must decide how many to buy.

Limiting the range of the values of the dependent variable in the second stage to only the positive values of those who consumed the apples leads to a nonzero mean of the disturbance term and to biased and inconsistent least squares estimators. A TOBIT model of the demand is often used in such situations to account for the bias that results when estimating the demand for purchasers only. The TOBIT model is described as follows:[62]

Let

$$Y_i^* = \alpha + \beta X_i + e_i^* \qquad (i=1,2,...,n) \tag{5-4}$$

be a regression for which all basic assumptions are satisfied. Let the dependent variable, Y^*, represent the consumption of some commodity (or an index of desire), X represent a vector of explanatory variables, β represent the vector of coefficients on X, and n is the number of households. For the households that consumed positive quantities of the commodity, Y^* is the actual quantity. For households that did not consume any of the commodity, Y^* represents an index of the "desire" to purchase the commodity.

For households that did not consume the good, Y^* is not observed and is recorded as zero. Thus, instead of observing Y_i^*, we actually observe Y_i, which is defined as

$$Y_i = Y_i^* \text{ if } Y_i^* > 0,$$
$$= 0 \quad \text{if } Y_i^* \leq 0.$$

Equation 5-1 then becomes

$$Y_i = \alpha + \beta X_i + e_i \tag{5-5}$$

where Y_i is truncated at zero and e is truncated at $-(\alpha+\beta X_i)$. The probability distributions of Y_i and e_i are both cut off and the probabilities are piled up at the cut-off

[62] The presentation of the TOBIT model borrows heavily from Kmenta (1986, 560-563).

point. The mean of Y_i is thus different from that of Y_i^*; the mean of e_i is different from the mean of e_i^*, which is zero. This is true whether the points for which $Y_i=0$ are or are not included in the sample (i.e., this is true whether the sample is truncated or censored).

The log-likelihood function for n observations is given as

$$L = \sum_{i=1}^{n} \{(1 - Z_i)\log F(\frac{-\alpha-\beta X_i}{\sigma}) + Z_i\,[-\frac{1}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(Y_i-\alpha-\beta X_i)^2\,]\} \tag{5-6}$$

where:

$$Z_i \quad \begin{aligned} &= 1 \quad \text{if } Y_i > 0, \\ &= 0 \quad \text{if } Y_i < 0 \end{aligned}$$

This function can be maximized to obtain the maximum likelihood estimates (MLE) of the model parameters.

However, the TOBIT model assumes that the factors that affect the decision to buy a product are the same as those that affect the quantity purchased. Several researchers (Haines, et al 1988; Yen 1993; Blaylock and Blisard 1992) use Cragg's (1971) double-hurdle model to explicitly account for the two-step process involved in consumption decisions. This model consists of estimating a PROBIT model for the indicator of whether the dependent variable is positive, and a truncated regression model for the non-limit observations. In this model, however, the relationship of the disturbance in the latent regression underlying the PROBIT model and that in the truncated regression is unclear (Greene 1992).

Heckman (1976, 1979) also proposed a two-step procedure to correct for the problem of censored data. Suppose that of all n observations there are m $(m<n)$ observations for which $Y_i^* > 0$. The regression equation for these observations is

$$Y_i=\alpha+\beta X_i+\epsilon_i \qquad (i=1,2,...m) \tag{5-7}$$

where Y_i and ϵ_i are truncated normal variables. Since the regression is only for those observations for which $Y_i^* > 0$, the conditional expectation of Y_i given $Y_i^* > 0$ is

$$\begin{aligned} E(Y_i|Y_i^*>0) &= \alpha+\beta X_i+E(\epsilon_i|Y_i^*>0) \\ &= \alpha+\beta X_i+E(\epsilon_i|\epsilon_i^*>-\alpha-\beta X_i) \\ &(i = (1,2,...m) \end{aligned} \tag{5-8}$$

Given that $\epsilon_i^* \sim N(0,\sigma^2)$, the mean of the corresponding truncated variable, ϵ_i, is

$$E(\epsilon_i|\epsilon_i^*>-\alpha-\beta X_i)=\sigma\lambda_i \tag{5-9}$$

where

$$\lambda_i=\frac{f(\frac{\alpha+\beta X_i}{\sigma})}{F(\frac{\alpha+\beta X_i}{\sigma})} \tag{5-10}$$

and f(*) represents the density and F(*) the cumulative distribution function of a standard normal variable. The variable λ_i is the inverse of the Mill's ratio. To allow for the non-zero mean of ϵ_i, the equation

$$Y_i=\alpha+\beta X_i+\sigma\lambda_i+\epsilon_i \qquad (i=1,2,\ldots,m) \tag{5-11}$$

is run on the m observations for which $Y_i^* > 0$. The error term in equation 5-8 then has a mean of zero.

If λ_i were observable, this equation would have a disturbance with zero mean and the least squares coefficients would be unbiased. Since λ_i is not observed, it must be estimated. The estimation procedure is as follows: (1) probit analysis is run using a dichotomous variable for consumption and non-consumption as the dependent variable, (2) equation 5-8 is estimated with λ_i as one of the explanatory variable using the m observations for which $Y_i > 0$. The estimators of α and β are consistent and asymptotically normal.

This research estimates a Heckman two-stage model and uses the results of the demand estimation in the second stage to calculate consumer surplus.

Estimating Consumer Surplus from the TOBIT Demand Equation

Hellerstein (1992) explains that substituting the estimated coefficients from the censored model (such as that described by the TOBIT or Heckman's two-stage procedure) into a linear functional form in order to calculate the consumer surplus is incorrect. When exogenous factors change, the individual's choke price changes, and this has non-linear effects on consumer surplus that are not accounted for if one uses the coefficients from the Heckman model and then integrates under the demand curve using those coefficients.

The correct measure of expected consumer surplus, is the following:

$$E[CS] = \int_{P_{obs}}^{P_{choke}} (\Phi * X\beta + \sigma\phi)\, dp \tag{5-12}$$

where σ is the standard deviation of the disturbance term, e, Φ and ϕ are evaluated at $(\beta X_i/\sigma_i)$, and P_{obs} is the observed price at which the integral is evaluated[63], and P_{choke} is the value at which demand approaches zero (selection of this price is described below). This measure of consumer surplus explicitly accounts for the fact that the choke price depends on the stochastic term.

As Hellerstein points out, since the integrand in equation 5-9 is strictly positive, the choice of a "choke" price is no longer obvious. This research follows Hellerstein and uses the cutoff price from the linear deterministic model: if the linear deterministic model is Y = $X\beta$, the cutoff price is $\dfrac{-(\beta X - \beta_{P_c} P_c)}{\beta_{P_c}}$.[64] This is the choke price we use when we estimate equation 5-9.

The value of equation 5-9 is calculated for each respondent, at a specified price for regular and certified apples. This calculation yields the total surplus associated with the purchase of certified apples. Since the dependent variable in the demand equation (equation 5-11 below) is the quantity of certified apples purchased in a fall season; the generated surplus measure is the surplus associated with the purchase of certified apples

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[63] The choice of the observation price is described in chapter 4.

[64] Hellerstein (1992) notes that this is not the price at which expected demand goes to zero, and is therefore not necessarily better than some other value (such as the maximum price observed in the sample).

in the fall quarter. The surplus per pound of certified apples is the fall surplus divided by the expected number of apples bought in the fall season. This amount is estimated using the integrand of equation 5-9.

Estimation

The general two-stage model of demand for certified apples estimated in this research is the following:

<u>Stage 1: PROBIT</u>

The following PROBIT model is run to determine the factors that affect the decision to select certified apples.

$$Z = \alpha_o + \alpha_{p_c} p_c + \alpha_{p_r} p_r + \alpha_{\pi^r} \pi^r + \alpha_{\Delta\pi} \Delta\pi + \alpha_{\epsilon^r} \epsilon^r + \alpha_{\Delta\epsilon} \Delta\epsilon + \alpha_M M + \alpha_S S + e$$

<u>Stage 2: OLS</u>

For households that choose certified apples:

$$Q = \beta_o + \beta_{p_c} p_c + \beta_{p_r} p_r + \beta_{\pi^c} \pi^c + \beta_{\Delta\epsilon} \Delta\epsilon + \alpha_M M + \alpha_{S'} S' + e$$

where:

Z	=	a dummy variable defined as: Z=1 if $Y_i^* > 0$ (the household buys certified apples), Z=0 if $Y_i^* \leq 0$ (the household does not buy certified apples).
Q	=	the quantity of apples consumed
α_o	=	constant term in PROBIT equation
β_o	=	constant term in the demand equation
p_c	=	the per-pound price of certified apples
p_r	=	the per-pound price of regular apples

π^r	=	perceived baseline probability of an adverse health effect resulting someday because of pesticide residues in food when one consumes regular apples
$\Delta\pi$	=	perceived change in the probability of an adverse health effect resulting someday because of pesticide residues in food when one consumes certified apples
ϵ^r	=	perceived ambiguity about π^r
$\Delta\epsilon$	=	perceived change in ambiguity about π^r when switching to certified apples
M	=	Income
S	=	demographic characteristics of the household related to choice of apple
S'	=	demographic characteristics of the household related to the quantity of apples bought
e	=	disturbance term

The next section describes various measures of the variables in the two-stage model that were solicited from survey respondents.

Variable Definitions

Dependent Variables

Z	=	a dummy variable defined as: $Z=1$ if the household selected certified apples), $Z=0$ if not.
Q	=	quantity of apples consumed in a fall season. The survey asked respondents about their apple-purchase intentions for a given shopping occasion. This variable is constructed by extrapolating the quantity purchased on each occasion to the quantity purchase in the fall based on information obtained in the survey about respondents general apple-buying patterns.

Independent Variables

<u>Measures of π^r</u>

π^r	=	Response to the question "suppose there were a million people from households like yours who did nothing to reduce or avoid pesticide residues in food. What do you think the chances are

that someone from one of these households would have a health problem someday because of pesticide residues in food?" Although the response categories are discrete choices ranging from 0 to one, the variable is treated as a continuous variable. (Corresponds to Q4)

π^r(VLCTH) = Qualitative response to the question "suppose someone from a household like yours did nothing at all to reduce or avoid pesticide residues in food. What do you think the chances would be that someone from that household will have a health problem someday because of pesticide residues in their food?" This is a dummy variable that takes the value of 1 if the respondent answered "very likely," or "certain to happen," and the value of 0 if the respondent gave any other response. (Created from responses to Q2).

π^r(SUSL) = Qualitative response to the same question as for π^r(VLCTH). This is a dummy variable that takes the value of 1 if the respondent answered "somewhat unlikely," or "somewhat likely," and the value of 0 if the respondent gave any other response. (Created from responses to Q2)

<u>Measures of $\Delta\pi$</u>

$\Delta\pi$(ABS) = perceived (absolute) change in the probability of an adverse health risk when switching from regular apples to certified apples

$\Delta\pi$(%) = perceived (percentage) change in the probability of an adverse health risk when switching from regular apples to certified apples

$\Delta\pi$(%OWN) = The amount of risk reduction (in percentage terms) respondent believes he/she gets through his/her own actions (washing, peeling, etc.) (Corresponds to Q7)

<u>Measures of π^c</u>

π^c = perceived probability of an adverse health effect resulting someday because of pesticide residues in food when one consumes certified apples. Because perceptions of this probability were not asked directly in the survey, it is calculated as π^r-$\Delta\pi$(ABS).

<u>Measures of ϵ^r</u>

ϵ^r(SURE) = The survey asked people how sure they were about their risk estimate. The response categories were "very sure," "somewhat sure," "somewhat unsure," and "very sure." This variable is a dummy variable created from the responses to that question. ϵ^r(SURE) has a value of 1 if the response was "somewhat unsure," or "very unsure;" 0 otherwise. (Created from answers to Q5)

ϵ^r(NTRSTSTD) = The survey asked respondents whether they "strongly agree," "somewhat agree," "somewhat disagree," or "strongly disagree" with the statement "I trust that once the federal standards [for pesticide residues] are set, all the food I buy will meet those standards." This variable takes a value of one if the respondent answered "somewhat disagree," or "strongly disagree," and 0 otherwise. (Created from answers to Q9)

ϵ^r(QUAL) = Same as ϵ^r(SURE) but this variable is the "sureness" associated with the qualitative, rather than quantitative measure of risk. (Created from Q3a).

ϵ^r(VSEFF) = The survey asked respondents "suppose the federal government did testing and certifying [of pesticide residue levels]. How effective do you think such a program would be in ensuring that foods had no pesticide residues above federal standards [or, that foods had been produced without pesticides?" This variable is a dummy variable that has a value of 1 if the respondent said "very effective" or "somewhat effective;" 0 otherwise. (Created from Q12).

<u>Measures of $\Delta\epsilon$</u>

$\Delta\epsilon$ = The survey did not ask respondents about their perceptions of the changes in ambiguity when switching to the certified apples. This variable is a proxy for changes in ambiguity. It is an interaction term created by multiplying the variables ϵ^r(VSEFF) and ϵ^r(SURE) together. If the value is 1, the respondent perceives a higher level of ambiguity reduction than if the value is 0.

<u>Price Variables</u>

p_r = Each respondent was given one of 40 price combinations for regular and certified apples. This variable is the per pound price of regular apples the respondent was given.

p_c = The per pound price of certified apples the respondent was given.

Demographic Variables in S and S′

M	=	Household's annual (1991) income before taxes. Although the responses were categorical, we treat income as a continuous variable, using the midpoint of the range as the income. (Corresponds to Q35, Q35a, Q35b, Q35c, Q35d, Q35e, and Q35f)
HHSIZE	=	The number of household members in the respondent's household. (Corresponds to Q31, Q31a, Q31b, and Q31c)
SCHOOL	=	The number of years of education of the respondent. Respondents were asked the highest level of education they had finished. These data were converted to years of education using the number of years that level would most likely represent. (Corresponds to Q34)
UND18	=	A dummy variable indicating the presence or absence of children under the age of 18 in the household. The variable takes a value of one if the household had at least one member under the age of 18; 0 otherwise. (Created from answers to Q31 and Q31a)

Testing the Hypotheses

This section discusses how the estimated coefficients from the model are used to test the hypotheses developed in chapter 3.

Hypotheses

Hypothesis 1. The marginal value of a decrease in the mean probability of an adverse health outcome (when ambiguity present) is positive.

If this hypothesis is true, then the higher the perception of risk reduction ($\Delta\pi$) associated with the certified apples, the more likely one would be to purchase the certified apples. We therefore expect the coefficient on the variable that measures $\Delta\pi$ to be positive in the PROBIT model. This hypothesis also suggests that the coefficient on π^c in the demand equation for certified apples should be negative, as a higher π^c, holding baseline risk constant, would mean lower risk reduction.

Hypothesis 2. The marginal value of a decrease in ambiguity is positive.

If the marginal value of a decrease in ambiguity is positive, then we would expect that a perception of ambiguity reduction would increase the probability of selecting the certified apples (the coefficient on $\Delta\epsilon$ should be positive in PROBIT model). Similarly, a perception of ambiguity reduction should increase the quantity of certified apples purchased (the coefficient on $\Delta\epsilon$ should be positive in demand equation).

Hypothesis 3. The WTP for certification **decreases** with initial ambiguity, holding ambiguity reduction, baseline risk, and risk reduction constant.

The higher the perception of baseline ambiguity, the less likely one should be to buy certified apples (coefficient on measure of ϵ^r should be positive in the PROBIT equation).

Hypothesis 4. The WTP for certification **increases** with initial risk.

People who perceive high risks from pesticide residues should be more likely to choose the certified apples. We would thus expect the coefficient on π^r to be positive in the PROBIT model.

Estimation Results

Factors Influencing the Decision to Purchase Certified Apples

The results of three PROBIT specifications are presented in Table 5-10. In the three models presented, the most important variables (based on significance level) influencing the decision to purchase the certified apples seem to be the prices of the two apples (certified and regular), and the presence of children in the household under the age of 18. The higher the price of the regular apples, the more likely it is that the respondent will buy certified apples; the higher the price of the certified apples per pound, the less likely they are to choose certified apples. The presence of children under the age of 18 in the household increases the likelihood that the household will purchase the certified apples.

Risk Reduction

All three probit models indicate that risk **reduction** from the certification ($\Delta\pi(\%)$) and the risk reduction achievable through one's own actions ($\Delta\pi(\%OWN)$) are important determinants the decision to buy the certified apples. As expected, the more risk reduction one perceives one gets from the certified apple, the more likely he/she is to purchase the certified apple, holding the **initial** risk level constant. Similarly, the more risk reduction people think they can get from their own actions, the less likely they are to buy the certified apples, suggesting that the risk reduction one gets from one's own actions and the risk reduction one gets from certified apples are substitutes. If they were complements, people would continue to undertake their own actions, even though they acquired additional risk reduction from the certification, and the variable

Table 5-10: PROBIT Results

	MODEL 1	MODEL 2	MODEL 3
Dep Var:	Z	Z	Z
Variable	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
α_0	0.29 (0.51)	0.15 (0.51)	-0.19 (0.53)
p_r	2.27*** (0.60)	2.19*** (0.60)	2.07*** (0.60)
p_ϵ	-2.68*** (0.54)	-2.62*** (0.54)	-2.45*** (0.53)
SCHOOL	0.06** (0.03)	0.06** (0.03)	0.06** (0.04)
INCOME	0.00001** (0.000003)	0.00001** (0.000003)	0.00001** (0.000003)
UND18	0.42*** (0.12)	0.40*** (0.12)	0.39*** (0.12)
π^r	0.32 (0.26)	0.29 (0.26)	
π^r(VLCTH)			0.53** (0.21)
π^r(SUSL)			0.42** (0.21)
$\Delta\pi$(%)	0.50** (0.23)	0.54** (0.23)	0.49** (0.23)
$\Delta\pi$(%OWN)	-0.56** (0.24)	-0.49** (0.24)	-0.43* (0.24)
ϵ^r(SURE)	-0.35* (0.22)		
$\Delta\epsilon$	0.44* (0.24)	-0.42 (0.28)	
ϵ^r(QUAL)			-0.24* (0.14)
ϵ^r(NTRSTSTD)		0.19 (0.15)	
ϵ^r(VSEFF)		0.14* (0.07)	
% of buying HHs	72%	72%	73%
Log (L)	-289.39	-290.95	-295.88
χ^2	67.71	68.16	67.00
Pseudo R^2	0.10	0.10	0.10
% correct predictions	75	74	73

* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

$\Delta\pi$(%OWN) would not be significantly different from zero in determining the choice of apple.

Ambiguity Reduction

The CVM survey did not explicitly ask respondents for their perceptions of the reduction in ambiguity associated with switching from regular to certified apples. However, we assume that among all respondents, those who have more baseline ambiguity **and** who think that a certification program run by the federal government would be effective would achieve the highest level of ambiguity reduction when switching to the certified apples. This is tested using the variable $\Delta\epsilon$ in model 1 and model 2. This variable is positive and significant in model 1, indicating that ambiguity reduction is important in determining consumers' choices. The variable is not significantly different from zero in model 2.

Further research is needed on ways of measuring perceptions of changes in ambiguity before conclusive statements about the effects of ambiguity reduction on choice can be made.

Baseline Risk

The effect of baseline risk is tested in model 1 and model 2 using a quantitative measure of initial risk perceptions (π^r). A qualitative measure of baseline risk is used in model 3 (π^r(QUAL). Although these models yield the expected positive sign on the coefficient for the baseline quantitative risk variable, the variable is not significantly different from zero in influencing respondents' choice of certified or regular apples.

We cannot, however, conclude that risk perceptions are not important in the choice process. It may be that a quantitative measure of risk such as π^r does not adequately measure peoples' concern about the health risks posed by pesticide residues on regular apples. Furthermore, because the survey asked respondents to imagine they were going shopping **intending to buy apples**, baseline risk may not affect the choice of which apple one buys while the **change** in risk does.

The qualitative measure of risk used in model 3 (π^r(QUAL) is positive and significant in determining consumers' choice of apple type. Relative to people who perceive a health effect resulting from pesticide residues in food to be "very unlikely" or "no chance," (as captured by the constant term) people who perceive the chance to be "somewhat unlikely," or "somewhat likely" (π^r(SUSL)=1) and people who perceive the chance to be "very likely," or "certain to happen" (π^r(VLCTH)=1) are more likely to purchase the certified apple. Even moderate concerns about the health risks from pesticide residues compels people to buy the certified apples. Although we would expect the quantitative and qualitative measures of risk to be highly correlated, the difficulty of putting a number on one's risk assessment (which does not apply to the qualitative assessment) may be the reason that the quantitative variable (π^r) does not capture the effect of concerns about pesticide residues on the demand for certified apples.

If people have different assessments of the risks from pesticide residues on regular apples for children than they do for adults, a dichotomous measure such as UND18 may better reflect consumers' concerns. Although the variable π^r should reflect this (since it is a risk assessment for the whole household), the variable UND18 may do a better job of distinguishing these dichotomous concerns. This would be consistent with the National Research Council (1993) finding that children face the greatest risk from pesticide residues in food (they consume more fruits and vegetables than do adults, unlike adults, they are subject to developmental effects, and they have a longer time span over which to accumulate residues in their system).

Baseline Ambiguity

The variables **ϵ^r(SURE)** and **ϵ^r(QUAL)** in model 1 and model 3 measure peoples' "sureness" about their estimate of the baseline risk. **ϵ^r(NTRSTSTD)** is the measure of peoples' trust that the standard set by the government for pesticide residues in food (whatever that may be) meets the standard for pesticide residues (**ϵ^r(NTRSTSTD)**=1 indicates a person does not trust that food meet the standards). Although hypothesis 4 suggests that the sign of the coefficient on **ϵ^r(SURE)** and **ϵ^r(QUAL)** should be negative, the expected sign on **ϵ^r(NTRSTSTD)** is unclear. We assume that people who mistrust that the food they buy meets the federal standards for pesticide residues have higher ambiguity (indicating that the sign of its coefficient should be negative). However, this variable probably also captures their higher risk perception as people who feel that food does not currently meet the standard probably perceive higher levels of pesticide residues in their food. The sign on the coefficient might then be positive. This variable probably confounds the two perceptions; and the expected sign of its coefficient remains undetermined.

Both "sureness" measures of ambiguity (**ϵ^r(SURE)** and **ϵ^r(QUAL)** in model 1 and model 3 are significant and negative at the 10% level; the "trust" measure of ambiguity in model 2 (ϵ^r(**NTRSTSTD**)) is not significantly different from zero. As was shown in chapter 3, the more ambiguity people feel about their risk estimate, the less likely they should be to buy the certified apple, since, if they are unsure about their risk estimate, they will be unsure about the risk reduction they will be getting with the certified apple.

Goodness of Fit

Several goodness of fit measures suggest that the three PROBIT models presented in Table 5-10 are all significant. A likelihood ratio test of the hypothesis that all the coefficients are zero shows that all three PROBIT models are highly significant. The χ^2 value for each model (67.71 with 10 degrees of freedom for model 1, 68.16 with 11 degrees of freedom for model 2, and 67.00 with 10 degrees of freedom form model 3) is well above the critical value at 0.001 level of significance. Furthermore, all three models make over 70% correct predictions. Although the pseudo R^2 are low for all the models, we hesitate to emphasize this measure of goodness of fit as Greene (1990) suggests that "values between zero and one have no natural interpretation" (Greene 1990, 682).

Because all three models fare equally well in the goodness of fit measures, the calculations of the willingness to pay for pesticide-residue certification is based on model 1.[65] This model uses the measure of ambiguity most closely related to the definition of ambiguity used throughout the text. The results in the other models do

[65] The second-stage estimation for both model 1 and model 2 is presented in Table 5-11.

provide, however, further evidence of the importance of ambiguity in the consumers' choice calculus.

Type of Certification

In all three models, the "type" of certification one received did not influence the decision to buy the apple. The decision to purchase the certified apples was not influenced by whether one received the "produced without pesticides" certification, or the "this product meets federal standards for pesticide residues" certification.[66]

This result could stem from two factors. The presence of the certification, regardless of the exact content, may be enough to assuage peoples' fears about pesticide residues. In other words, there is a sort of "warm glow" effect (Andreoni 1990, Kahneman and Knetsch 1992). People may be willing to pay for the certified apple as long as it gives them **some** improvement over the regular apples. The "quantity" of the improvement may not be important as long as people think they are getting **some** reduced risk.

[66] The effect of the label was tested using a dummy variable, CERT, which was 0 if the respondent received the "meets federal standards" label, and 1 if the respondent received the "produced without pesticides" label, in the PROBIT model. These results are presented in Appendix 5-2.

Factors Influencing the Demand for Certified Apples

This section discusses the results of the second stage demand estimation based on the first stage in model 1.[67] The results in Table 5-11 show that the most important factor determining the quantity of certified apples, once the decision to buy them has been made, is household size. In model 1 and model 2 household size (**HHSIZE**) is significant and positive. The models also demonstrate that the demand for certified apples is price and income inelastic. Price and income influence the choice to buy the certified apples, but once the decision to buy them has been made, people seem to buy the quantity based on the size of the household.

The risk associated with the certified apple (π^c) is significant in both models, although it is not the expected sign. We expected that higher perceived risk on the certified apples would compel people to buy fewer certified apples. However, this finding probably reflects the measurement of π^r rather than π^c. The survey did not ask respondents to directly state their perceptions of the risks from certified apples. Instead it asked for perceptions of the risk from regular apples and the percentage of perceived risk reduction when apples were labeled. The risk from the certified apples is calculated based on this information. Because perceived risk reduction is generally small, the constructed variable may be overwhelmed by the influence of the risk of regular apples, thus explaining the positive sign on π^c.

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[67] Because the results of the PROBIT analysis showed that people did not distinguish between the two labels when making their decision about certified apple, we estimate the demand for all certified apples together, i.e., we do not distinguish between the types of label.

Table 5-11: Second-Stage Demand Equation with Ambiguity measured as ϵ^r(SURE)

	MODEL 1	**MODEL 1**
Dependent Variable:	QC	QC
Variable	**Coefficient (standard error)**	**Coefficient (standard error)**
CONSTANT	15.40 (9.267)	19.52 (8.99)
p_r	22.18 (20.09)	11.03 (18.75)
p_c	-27.65 (20.09)	-15.11 (18.79)
HHSIZE	3.68*** (1.22)	3.41*** (1.18)
INCOME	0.0001 (0.00001)	0.0001 (0.00001)
π^c	30.22** (13.52)	29.74** (13.02)
$\Delta\epsilon$	-5.74 (4.20)	-5.50 (3.63)
λ	10.74 (12.79)	-0.95 (12.45)
Log (L)	-1889.38	-1894.23
Corrected std. error	32.6	31.9
Mean of LHS	26.1	26.1
Adjusted R^2	0.03	0.03

* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

Because the survey did not solicit the amount of ambiguity associated with the certified apple, the models use ambiguity reduction as an associated measure of the ambiguity. This variable is not significantly different from zero in determining the quantity of apples purchased in either model.

Although the explanatory variables do not explain very well the variation in the quantity purchased, we use the results of model 1 to calculate the willingness to pay for certification as discussed in the next section. Because the approached used to estimate consumer surplus depends on the results from both the PROBIT and the second-stage estimation, the WTP calculations are strongly influenced by the factors that affect the choice to buy certified apples.

Willingness to Pay for Certification

The estimates of the willingness to pay for certification are shown in Table 5-12 through Table 5-15. Table 5-12 shows the welfare measures on a "per pound" basis, Table 5-13 shows the measures on a "per year" basis. The measures of willingness to pay are based on the coefficients from Model 1 (both stages). The "base" row is the willingness to pay for certification using the observed values for all variables. Based on the data from this survey, we estimate that people are willing to pay $0.31 (32%) more per pound for the certified apple than what they pay for the regular apple. This is within the range of the estimates obtained in the van Ravenswaay and Hoehn study (1991) where they estimated the average added price per pound was between $0.24 and $0.38, depending on the exact content of the certification.

Table 5-12: Willingness to Pay for Certification and Sensitivity Analysis[68] ($ per pound, per household)

SCENARIO	**MODEL 1 (ambiguity measured with ϵ^r)**
Base Case	**$0.31**
Scenario 1	$0.28 (-10% from base)
Scenario 2	$0.32 (+3% from base)
Scenario 3	$0.31 (+0% from base)

Table 5-13: Willingness to Pay for Certification ($ per year, per household)

SCENARIO	**MODEL 1 (ambiguity measured with ϵ^r)**
Base Case	**$7.06**
Scenario 4	$9.92 (+41% from base)

Table 5-14: Changes in WTP due to Changes in Baseline Risk

Baseline Risk	**Willingness to Pay for Certification ($ Per Pound)**
$\pi^r \leq 0.00001$	$0.31 (+0% from base)
$0.00001 < \pi^r \leq 0.001$	$0.30 (-3% from base)
$\pi^r > 0.001$	$0.33 (+6% from base)

[68] The analysis is conducted at the following prices:

$0.98 for regular apples
$1.04 for certified apples

See text for discussion of price selection

Table 5-15: Changes in WTP for Certification due to Changes in Sureness

Sureness Level	Willingness to Pay for Certification ($ Per Pound)
Very Sure	$0.34 (+9% from base)
Somewhat Sure	$0.31 (+0% from base)
Somewhat Unsure	$0.28 (-10% from base)
Very Unsure	$0.26 (-16% from base)

The tables also show the estimates of willingness to pay for certification under various scenarios. We use these results to discuss the marginal willingness to pay for ambiguity and risk reduction. The scenarios apply the coefficients from the base model to the actual values of the variables, while changing the values of the risk or ambiguity variables. The scenarios are as follows:

Scenarios

Scenario 1. All consumers are either "very unsure" or "somewhat unsure" about their risk estimate

Scenario 2. All consumers are either "somewhat sure" or "very sure" about their risk estimate

Scenario 3. All consumers believe a federal program to test and certify food for pesticide residues would be either "very effective" or "somewhat effective."

Scenario 4. The chance of having an adverse health outcome someday because of pesticide residues in food is reduced by 0.000001.

The average willingness to pay for the certification on apples under scenario 1 is \$0.28. In this scenario everyone is either "very unsure" or "somewhat unsure." This is \$0.03 (or 10%) less than the under the base scenario in which 29% of the respondents were "very unsure" or "somewhat unsure." Baseline risk was not changed in this scenario, indicating that perhaps people simply want to know what they are getting in terms of safety when they buy apples. They get that with the certified apple; they may not be getting it with the regular apple. The results conform with the hypothesis that people with higher initial ambiguity should be willing to pay less for certification.

If all respondents felt sure about their estimates (they were either "somewhat sure" or "very sure" as in Scenario 2) willingness to pay for the certification increases by \$0.01 (+3%) from the base case and \$0.04 (+14%) from scenario 1 in which all respondents are "somewhat unsure" or "very unsure."

Scenario 3 shows that if everyone were convinced of the effectiveness of a federal program to test and certify food for residue levels, willingness to pay for the certified apple would be the same as in the base case (\$0.31 per pound).

To estimate the marginal value of a change in mean risk, we create a scenario in which the lifetime risk of having an adverse health effect from pesticide residues in food is reduced an additional one in a million (Scenario 4). We reestimate the willingness to pay assuming that the change in risk is increased in the amount that would reflect this change. The results in Table 5-13 show that people would be willing to pay an additional \$2.94 (+41%) per year for pesticide-residue certification on apples to acquire that level of risk reduction.[69] It should be noted that this risk reduction is a reduction in the **lifetime** risk of having a health problem someday because of pesticide residues in **all food**, not just the risk from pesticide residues on apples.[70]

Table 5-14 and Table 5-15 show that, as hypothesized, the willingness to pay for certification increases with baseline risk and decreases with baseline ambiguity.

Conclusions

The results presented in this chapter indicate that ambiguity may be an important factor influencing the consumption of certified apples. Perceptions of high baseline ambiguity probably drive the choice to buy the certified apples, but once that decision has been made, neither baseline ambiguity nor changes in ambiguity help determine the quantity purchased.

Respondents are willing to pay positive amounts (on average about $0.31 per pound, or a 32% premium) for certification that the apples they buy either meet federal standards for pesticide residues or have been produced without pesticides. The amount they are willing to pay seems to be influenced by the ambiguity as evidenced by the variation in the willingness to pay across perceived ambiguity levels. Unsureness about

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[69] The surplus is calculated on a "per fall" basis. We multiply this figure by 4 to get annual figures. Although the quantity of apples bought varies by seasons and is probably lower in seasons other than the fall, this calculation gives an upper-bound estimate.

[70] If we assume that apples are a constant proportion of the total diet, this figure can be interpreted as the amount consumers are willing to pay for risk reduction in apples that contributes to a total risk reduction from all foods of one in a million.

risk estimates for regular apples may avert people from purchasing the certified apples since they cannot be sure about the risk reduction they are getting.

Baseline risk perceptions, as they are quantitatively measured here, may not adequately capture peoples' concerns about the risks from pesticide residues. People seem to be worried about the effects of pesticide residues in food for children, as evidenced by the fact that households with children under the age of 18 are more likely to buy certified apples than other households. Although this should be captured by the risk estimate it is probably difficult for people to quantitatively estimate the risks they face from pesticide residues in food.

Measures of both baseline ambiguity and baseline risk are imperfect at best. When we use "trust that the standard is being enforced" as a proxy for ambiguity, for example, we are probably confounding two opposing forces. The trust in the standard variable probably captures the uncertainty about the risk estimate, but it probably also captures some of the perception of the change in risk associated with the certified apple. That is, when people feel that the standard is being enforced, they probably also feel that their risks are reduced (both baseline ambiguity and changes in risk are influenced by trust).

The measurement problem is probably the biggest obstacle researchers face in terms of trying to understand how risk and ambiguity perceptions affect the willingness to pay for certification and for reduced risk and ambiguity.

CHAPTER 6: POLICY IMPLICATIONS AND CONCLUSIONS

The goal of this research was to understand the effect of ambiguity on consumer decision making under uncertainty. To this end, several steps were necessary. First, we needed to define ambiguity. We then had to decide on a conceptual model of decision making under uncertainty that incorporates ambiguity and use the model to develop hypotheses about the effect of both risk and ambiguity on willingness to pay for pesticide-residue certification. We also needed to develop methods for measuring ambiguity. This chapter summarizes the conceptual and empirical findings of the research and develops policy implications based on these findings. It also discusses the issues related to survey design and accurate measurement of ambiguity. The chapter concludes with the future research needs this study has identified.

Conceptual Findings

This research defines ambiguity as uncertainty about the probability of an outcome. It can be characterized by the "spread," or the variance, of the second-order probability distribution of an outcome;[71] the higher the level of ambiguity one feels about his/her probability estimate, the wider the second-order probability distribution.

In traditional models of decision making under uncertainty (EU, for example), ambiguity is behaviorally insignificant. This results because people are assumed to use

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[71] Higher moments of the probability distribution such as the skewness and kurtosis may also characterize ambiguity. Here we assume the probability distribution around the mean probability is normally distributed and is therefore fully characterized by its mean and variance.

the Reduction of Compound Lotteries Axiom (RCLA) when processing multiple layers of risk. That is, if there is a probability distribution for the various probabilities that might characterize an outcome, the decision maker "reduces" the compound probabilities to a single probability by taking the "weighted average" of the possible probabilities, where the weights are the probabilities of those probabilities. The "spread" of the second-order probability distribution is then not important. However, several empirical and experimental studies, starting with Ellsberg (1961), have shown that peoples' decisions are affected by the presence of multiple layers of risk.

Following Segal (1987), this research assumes that decision situations that include both risk and ambiguity can be considered 2-stage lotteries in which the first stage is a lottery over the probability, and the second stage is a lottery over the outcome. Probability "certainty equivalents" (CEs), which give the probability that would make a decision maker just indifferent between facing the first-stage lottery over the probability and facing the second-stage lottery with the CE probability, are used to convert a two-stage lottery to a one-stage lottery.

Ambiguity then enters peoples' objective function in two ways: (1) through the perceived amount of ambiguity and (2) through the individual's attitude toward ambiguity (the shape of the weighting function, $\bar{f}$). Here we assume in that decision makers are ambiguity averse ($\bar{f}$ is concave), i.e., they prefer known to unknown probabilities. Ambiguity has the effect of increasing the overall riskiness of a prospect, but its effect on decision making is distinct from standard risk aversion because of the shape of the weighting function.

We use Segal's method of incorporating ambiguity into a model of decision making to develop the hypotheses that (1) the willingness to pay for certification about pesticide residues is positive, (2) the willingness to pay for residue certification increases with baseline risk and decreases with baseline ambiguity, and (3) the marginal value of a reduction in either risk or ambiguity is positive.

Ambiguity affects consumers' choices about certified and regular apples through both baseline, or initial, ambiguity and through the perceived difference in the ambiguity associated with the two types of apples. This study hypothesized that people with higher **initial** ambiguity (higher ambiguity associated with the regular apples) would be willing to pay more for certified apples than people with lower initial ambiguity. Higher initial ambiguity reduces the likelihood that one is actually getting significant risk reduction from the certified apple.

Consumer choice is also affected by the perception of the **change** in ambiguity that is associated with the certified apple. A second hypothesis was that people who perceived more ambiguity reduction from the certified apple would be willing to pay more for the certification than people who do not believe the certification reduces ambiguity.

Furthermore, both **baseline** risk and **changes** in risk should affect consumers' choices about certified apples. People who perceive higher baseline risk should be willing to pay more to for certification about pesticide residues. And people who perceive that they get more risk reduction from the certification, should be willing to pay more than people who perceive lower risk reduction.

Empirical Findings

The conceptual framework developed in chapter 3 suggests that consumers make decision about purchasing apples in two-stages. First they decide whether to buy the certified or the regular apples. Once that decision has been made, they decide how apples to buy. This research uses Heckman's two stage model to allow the factors that affect choice to differ from the factors that affect quantity.

To empirically test the hypotheses developed in chapter 3, this research used the results of a contingent valuation survey of 1000 Michigan households' attitudes about pesticide residues and purchase intentions for apples with and without pesticide-residue certification.

The empirical results of the two-stage model show that people are willing to pay approximately 31 cents per pound above what they pay for regular apples to get the pesticide-residue certification. The regular apples and the certified apples are identical except for the certification indicating that the apple has been tested and certified to either meet federal standards for pesticide residues or to have been produced without pesticides.

As predicted by theory, willingness to pay for certification decreases with baseline ambiguity. People who are "very unsure" about their risk estimates are willing to pay $0.08 less per pound for the certified apples (a 24% discount) than the people who are "very sure." We cannot reject the hypothesis that willingness to pay for certification decreases with baseline ambiguity.

Although the survey did not directly measure the change in ambiguity associated with the certified apple, the evidence presented in this research suggests that reducing ambiguity has value. When all respondents are sure of their risk estimates (a decrease in ambiguity) WTP increases by $0.04 (+13%) per pound of apples relative to the case where all respondents are unsure. These findings hold constant the level of initial risk and the amount of risk reduction acquired from the certified apples. This evidence suggests that some of what people are willing to pay for the pesticide-residue certification stems from the uncertainty they feel about the potential health risks from pesticide residues in food.

As the third hypothesis predicted, people are willing to pay positive amounts to reduce the risks from pesticide residues. The empirical results suggest that people are willing to pay up to $2.92 (+41%) per year to reduce the lifetime risk of an adverse health outcome from pesticide residues by 1 in a million.

The PROBIT analysis of the factors influencing the decision to buy certified apples suggests that ambiguity is important in the decision to buy certified apples. People with higher baseline ambiguity (as measured for the qualitative risk estimate) were less likely to buy the certified apples than those with higher initial ambiguity. However, other factors such as the risk reduction associated with certification, the reduction in risks that one can obtain from one's own actions, the prices of regular and certified apples, household income, and the presence of children under the age of 18 also influence the decision to purchase the certified apples.

Policy Implications

The empirical findings suggest that ambiguity is a potentially important concern to consumers. There is little doubt that consumers feel some uncertainty about the risks they face from pesticide residues in apples: 29% of the survey respondents said they were either "somewhat unsure" or "very unsure" about their risk estimate. Similarly, a large percentage of respondents said they do not trust that the government sets the same standards they would, nor do they trust that once the standards are set, all foods meet those standards.

There are several sources of ambiguity about the risks from pesticide residues that need to be distinguished before any policy recommendations about ambiguity can be made. Some ambiguity stems from the current scientific uncertainty about the health effects of pesticide residues in food. There are varying expert opinions about the health risks from pesticide residues. If consumers are bombarded with information on the varying opinions, it is unlikely that their ambiguity will be reduced. To diminish ambiguity from this source, policy makers could develop policies to foster scientific consensus (by holding conferences, for example).

Another source of ambiguity for consumers is the lack of information they have about the current levels of pesticide residues in food. Although this information is theoretically obtainable, it is costly to obtain. However, currently known information about the levels of pesticide residues in food could potentially be offered to consumers in a clear and informative way that would reduce ambiguity. Similarly, information about the current standards for pesticide residues in food, information about whether those standards are being met, and information about the ways people can reduce the amount of residues they ingest, would all reduce consumers' ambiguity and increase their welfare.

Consumers often receive conflicting information from the media about the health risks from pesticide residues. Consumers are reassured, for example, that domestically produced goods currently meet the standards for pesticide residues. Yet they are also informed of the "circle of poison" in which pesticides that are banned for use in the US return to consumers via imported produce. This conflicting information increases the ambiguity people feel about their risk estimates.

The government also needs some "public relations" work to convince the public that it is taking their best interests into account when making policy decision about pesticides. Consumers need to feel confident that the standards for pesticide residues in food reflect safe levels and not levels that protect special interests.

This research suggests that people are willing to pay significant amounts to receive the signal that something has been done about pesticide residues to protect their health. It does not seem to matter what the exact content of the certification is ("warm glow" effect). The difference in willingness to pay across ambiguity levels and across risk levels suggests that a simple policy stating that a product meets the current standards for pesticide residues could increase consumer welfare by reducing both ambiguity and risks. Although testing and certifying products would be required for such a policy, the cost of such a policy would probably be low since most foods already meet the standards.

Survey Design Issues

The contingent valuation survey used in this research was carefully designed to ensure valid results about the willingness to pay for pesticide-residue certification. It created a shopping scenario that was within the respondents' realm of experience, questions were worded with careful attention to how they would be interpreted, and extensive pretests were conducted to guarantee that the survey generated meaningful data.

An important aspect of this survey was that substitution possibilities were accounted for by allowing respondents to choose between regular and certified apples. This is a realistic choice scenario that a consumer might actually face someday, and is an improvement over most surveys which consider only one product at a time.

The survey was also designed to minimize the likelihood that people would have difficulty making decisions about the products offered. Most people buy apples; it is easy for them to accurately predict their purchasing behavior.

Although contingent valuation surveys commonly ask respondents to directly state their willingness to pay for specific goods or services, this research did not use this approach. Instead, the survey asked respondents how many apples they would likely buy under different scenarios. It The information is then used to estimate willingness to pay for risk reduction. Since consumers are more likely to have to make market choices than to be asked to pay directly for reduced risks, the market scenario is more understandable, plausible, and meaningful to respondents.

Measurement Issues

It is difficult to conceptualize measures of ambiguity that capture the actual ambiguity people feel, since ambiguity is defined as the "spread" of the probability distribution. The variance of the second-order probability distribution of an outcome would be the most appropriate measure. However, without knowing the shape of the respondents' second-order probability distribution, it is difficult to measure ambiguity. The proxies developed in this research serve as indicators of ambiguity levels that can be used in the absence of more accurate measures.

This research developed three proxies for "baseline" ambiguity that are likely to be highly correlated with the actual "baseline" ambiguity. The first of these proxies is peoples' "sureness" about their estimate of the risks associated with regular apples. The survey asked people how **sure** they were of their estimate of the probability that someone from a household like theirs would have a health problem someday because of pesticide residues in food. We assume that people who are more "sure" about their risk estimate have lower ambiguity. However, it is impossible to know the exact relationship between actual ambiguity and its proxies.

The "sureness" proxy was also used to measure peoples' ambiguity about their qualitative perception of risk.

The third proxy developed was peoples' trust that the standards for pesticide residues for food were being met. Although this variable does not **measure** ambiguity, it **influences** ambiguity - the less trust one has that the standards are being met, the higher the ambiguity one will have about the risk estimate. This variable probably also influences the mean probability: people who do not trust that the standard is being met have a higher mean risk than those who do.

These proxies were developed for the **baseline** ambiguity associated with the certified apples. The survey did not develop any explicit measures of the **changes** in sureness or trust about foods meeting the standard when moving from the regular to the certified apples. It did, however, construct an indicator of the change in ambiguity by interacting sureness level with perceptions of the effectiveness of a federal program to test and certify products for pesticide residue levels. This variable was significant in determining the choice of apple (although it did not help explain the quantity consumed). This finding highlights the need to further develop measures of consumers' perceptions of the change in ambiguity.

When we use proxies for ambiguity, we are not guaranteed that we are measuring ambiguity. When we ask people about their level of trust that foods meet the standards for pesticide residues, for example, it is difficult to know that we are not getting a measure that captures both risk **and** ambiguity.

Future Research Needs

There is enough accumulated theoretical and empirical evidence to indicate that ambiguity is an important input into consumer decision making under uncertainty. The biggest challenge to researchers working in this area is to develop measures of ambiguity that accurately reflect the variance of the second-order probability distribution of an outcome. "Laboratory-type" experiments probably offer the most promising means to explore methods for building a probability distribution for probabilities. It is unlikely that direct questioning of consumers will yield satisfactory measures of ambiguity.

It would be helpful to understand more clearly the factors influencing consumers' ambiguity levels; we could then target trouble spots more effectively when trying to reduce ambiguity. This hinges, however, on the development of accurate measures of ambiguity.

This research has assumed a relationship between the proxies for ambiguity and actual ambiguity. More research needs to be done to strengthen these assumptions.

This research was designed to examine whether ambiguity is a factor affecting WTP for certification. The next step is to develop a measure of peoples' perceptions of the ambiguity associated with certified apples. The resources needed to develop this information were not available at the time of the survey. However, the results of this research suggest that it would be worthwhile to do so. It is necessary to have more information on these perceptions in order to accurately estimate WTP to reduce ambiguity.

All of the results of this research rest on the assumption that people are ambiguity averse. There are some situations, however, where ambiguity might be desirable. Methods for gauging peoples' attitudes toward ambiguity need to be developed in order to more effectively capture the effects of ambiguity on decision making.

The results are also contingent upon the assumption that the RDEUWA model is the appropriate representation of decision making. Future research needs to explore the implications of introducing ambiguity into other generalized utility models to see if the derived hypotheses are the same as the ones developed here.

Another approach to understanding the importance of ambiguity is to assume that it affects the formulation of risk estimates. Bayesian analysis, for example, offers an approach to thinking about how ambiguity enters the process of risk estimation (Viscusi and O'Connor 1984, Eom 1994) Unlike the classical approach to uncertain events where one tests hypotheses using the sampling distributions of a selected test statistic, Bayesian analysis relies on posterior distributions. One starts with a prior probability distribution over various states of nature. The decision maker then revises this distribution in light of new observations. The revised distribution yields the posterior distribution, which is then used in combination with a utility function as the basis for decision making. Probability distributions over probabilities could be revised in light of new information about risks to arrive at posterior probability distributions over probabilities.

Ambiguity may also be a "dimension" of risk that is not captured by the mean risk assessment, but is nonetheless an important input into the decision making process under uncertainty. Dimensions of risk are characteristics of the risk scenario that affect choice. Other than ambiguity, these might include the size of the severity of the consequences, immediacy of effect, and voluntariness of risk (Slovic, et al 1990). This should be explored as an approach to thinking about ambiguity.

This research has focused solely on the implications of ambiguity for consumer choice. However, ambiguity also plays an important part in other areas concerned with risk. Techniques for risk assessment, for example, are affected by how ambiguity is handled. Often, each step of the assessment is fraught with uncertainty. It is not clear, for example, exactly how to extrapolate findings in laboratory animals to what we should expect in humans. Analysts have methods of handling uncertainty about risk estimates. They use "safety factors" when assessing the risks. They might multiply the assessed risk by 100, or 1000, just to be "safe," for example. However, all the uncertainty about the risk assessment is obscured when scientists report a "crisp" estimate of risk. There is no acknowledgement of the uncertainty about the risk assessment. More research needs to be undertaken about how best to assess ambiguous risks, and how to communicate ambiguity about risk estimates to the public.

Ambiguity promises to be an important area of research for gaining insights into decision making under uncertainty. Only with further research on the best way to conceptualize, measure, and incorporate it into a model of choice can we expect to more thoroughly understand its importance in choice.

APPENDICES

APPENDIX 3-1: THE MARGINAL VALUE OF A CHANGE IN RISK

$$D = v_h(p_y,p_r,p_c,M)\bar{f}(\pi^c + \gamma^1\epsilon^c) + v_h(p_y,p_r,p_c,M)\sum_{i=2}^{m}[\bar{f}(\pi^c + \gamma^i\epsilon^c) - \bar{f}(\pi^c + \gamma^{i-1}\epsilon^c)]\bar{f}(\sum_{j=i}^{m} q^j) \tag{3-1}$$

We are interested in $-\left[\frac{\partial CV}{\partial \pi^c}\right]_{\pi^r}$

This can be written as $-\left[\frac{\partial CV}{\partial \pi^c}\right]_{\pi^r} = \left[\frac{D\pi^c}{D_{CV}}\right]_{\pi^r}$

$$= \frac{v_h(p_y,p_r,p_c,M-CV)\dfrac{\partial\bar{f}(\pi^r + \gamma^1\epsilon^r)}{\partial\pi^r} + v_h(p_y,p_r,p_c,M-CV)\sum_{i=2}^{m}[\dfrac{\partial\bar{f}(\pi^r + \gamma^i\epsilon^r)}{\partial\pi^r} - \dfrac{\partial\bar{f}(\pi^r + \gamma^{i-1}\epsilon^r)}{\partial\pi^r}]\bar{f}(\sum_{j=i}^{m} q^j)}{v_h'\bar{f}(\pi^r + \gamma^i\epsilon^r) + v_h'\sum_{i=2}^{m}[\bar{f}(\pi^r + \gamma^i\epsilon^r + \bar{f}(\pi^r + \gamma^{i-1}\epsilon^r)\bar{f}(\sum_{j=1}^{m} q^j)} \tag{3-2}$$

where $v_h' = \dfrac{\partial v_h(p_y,p_r,p_c,M-CV)}{\partial CV}$

If $\bar{f}$ is concave and symmetrical, the marginal utility of income is positive, and $v_h() < 0$, this expression will be positive.

APPENDIX 3-2: THE MARGINAL VALUE OF A CHANGE IN AMBIGUITY

The RDEUWA can also be written as:

$$v_h(p_y,p_r,p_c,M-CV)\sum_{i=1}^{m-1}\bar{f}(\pi^c+\gamma^i\epsilon^c)[\bar{f}(\sum_{j=1}^{m}q^j)-\bar{f}(\sum_{j=i+1}^{m}q^j)]+v_h(p_y,p_r,p_c,M-CV)\bar{f}(\pi^c+\gamma^m\epsilon^c) \tag{3-1}$$

$-\left[\dfrac{\partial CV}{\partial \epsilon^c}\right]_{\epsilon}$ is then

$$\frac{v_h(p_y,p_r,p_c,M-CV)\sum_{i=1}^{m-1}\dfrac{\partial\bar{f}(\pi^c+\gamma^i\epsilon^r)}{\partial\epsilon^r}[\bar{f}(\sum_{j=1}^{m}q^j)-\bar{f}(\sum_{j=i+1}^{m}q^j)]+v_h(p_y,p_r,p_c,M-CV)\dfrac{\partial\bar{f}(\pi^c+\gamma^m\epsilon^r)}{\partial\epsilon^r}}{v_h'(\sum_{i=1}^{m-1}\dfrac{\partial\bar{f}(\pi^c+\gamma^i\epsilon^r)}{\partial\epsilon^r}[\bar{f}(\sum_{j=1}^{m}q^j)-\bar{f}(\sum_{j=i+1}^{m}q^j])+v_h'\dfrac{\partial\bar{f}(\pi^c+\gamma^m\epsilon^r)}{\partial\epsilon^r}} \tag{3-2}$$

where $v_h' = \dfrac{\partial v(p_y,p_r,p_c,M-CV)}{\partial CV}$

If $\bar{f}$ is concave and symmetrical, the marginal utility of income is positive, and $v_h() < 0$, this expression will be positive.

APPENDIX 3-3: THE EFFECT OF BASELINE RISK ON WTP FOR CERTIFACTION

To develop the effect of changes in baseline risk on WTP for certification, we find the sign of

$$\frac{\partial\left[-\dfrac{\partial CV}{\partial \pi^c}\right]_{\pi^r}}{\partial \pi^r}.$$

That is, we need to find the sign of the following:

$$\frac{[bottom\ of\ eq\ 3\text{-}2]\,[-v_h(M-CV)(\dfrac{\partial^2\bar{f}(\pi^r+\gamma^1\epsilon^c)}{\partial \pi^{r2}}) - v_h(M-CV)(\sum_{i=2}^{m}(\dfrac{\partial^2\bar{f}(\pi^r+\gamma^i\epsilon^c)}{\partial \pi^{r2}} - \dfrac{\partial^2\bar{f}(\pi^r+\gamma^{i-1}\epsilon^c)}{\partial \pi^{r2}}))] - [top\ of\ eq\ 3\text{-}2](v_h'\dfrac{\partial\bar{f}(\pi^r+\gamma^1\epsilon^c)}{\partial \pi^r} + v_h'(\sum_{i=2}^{m}\dfrac{\partial\bar{f}(\pi^r+\gamma^i\epsilon^c)}{\partial \pi^r} - \dfrac{\partial\bar{f}(\pi^r+\gamma^{i-1}\epsilon^c)}{\partial \pi^r})}{[bottom\ of\ eq3\text{-}2]^2}$$

If $\bar{f}$ is concave and symmetrical, the marginal utility of income is positive, and $v_h() < 0$, this expression will be positive.

APPENDIX 5-1: SURVEY INSTRUMENT

[Please note: all skip patterns and split-sample variations have been removed for better readability of survey]

Hello, is this ________________ (confirm phone number)

My name is __________________ and I am calling from the Center for Survey Research at Michigan State University.

We are conducting a study on behalf of the Department of Agricultural Economics at Michigan State University regarding pesticide residues in food.

According to our sampling design, I need to speak to the person in the household, who is at least 18 years of age, who does the most grocery shopping. Would that be you?

Before we begin, let me tell you that any information you give me will be kept strictly confidential. Let me also tell you that this interview is completely voluntary. Should we come to any question that you don't want to answer, just let me know and we'll go on to the next question.

Throughout the study, we will be asking for your opinions in terms of the food you buy for your household. Your household includes yourself, your dependents, and persons with whom you share income and household living expenses. We will also be talking about pesticide residues in food. Pesticides are used to control insects, diseases, and other pests that spoil food. To protect consumers' health, the federal government sets standards that limit the amount of pesticide residues that may be in food sold in the U.S.

Q1 In terms of pesticide residues, how confident are you that the food your household eats is safe?

Would you say you are completely confident, mostly confident, somewhat confident, or not confident at all?

<1> COMPLETELY CONFIDENT
<2> MOSTLY CONFIDENT
<3> SOMEWHAT CONFIDENT
<4> NOT CONFIDENT AT ALL

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q2 Suppose someone from a household like yours did nothing at all to reduce or avoid pesticide residues in food. What do you think the chances would be that someone from that household will have a health problem someday because of pesticide residues in their food?

Would you say there is no chance, it is very unlikely, somewhat unlikely, somewhat likely, very likely, or certain to happen?

<1> NO CHANCE
<2> VERY UNLIKELY
<3> SOMEWHAT UNLIKELY
<4> SOMEWHAT LIKELY
<5> VERY LIKELY
<6> CERTAIN TO HAPPEN

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

3a How sure are you that there is ______ of a health problem because of pesticide residues in food? (blank is filled with respondents answer from Q2)

Would you say you are very sure, somewhat sure, somewhat unsure, or very unsure?

<1> VERY SURE
<2> SOMEWHAT SURE
<3> SOMEWHAT UNSURE
<4> VERY UNSURE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q4 Now I would like to get a better idea about what you mean by ______ (blank is filled with respondents answer from Q2). Suppose there were a million people from households like yours who did nothing to reduce or avoid pesticide residues in food. What do you think the chances are that a person from one of these households would have a health problem someday because of pesticide residues in food?

Would you say 1 person in a million, 1 in 100,000, 1 in 10,000, 1 in 1,000, 1 in 100, or 1 in 10?

<1> 1 PERSON IN A MILLION
<2> 1 IN 100,000
<3> 1 IN 10,000

<4> 1 IN 1,000
<5> 1 IN 100
<6> 1 IN 10

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q5 How sure are you that the chances are _______ (blank is filled with respondents answer from Q4).

Would you say you are very sure, somewhat sure, somewhat unsure, or very unsure?

<1> VERY SURE
<2> SOMEWHAT SURE
<3> SOMEWHAT UNSURE
<4> VERY UNSURE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q6 Is there anything you usually do to reduce or avoid pesticide residues in your food? (open-ended, field coded)

<1> YES:specify
<5> NO

<98> DON'T KNOW
<99> REFUSED

Q7 Suppose someone did the same things you usually do to reduce or avoid pesticide residues in food.

What percent do you think that would reduce the chances of a health problem happening some day?

<0-100> ENTER EXACT PERCENT

<998> DON'T KNOW/NO OPINION
<999> REFUSED/NO ANSWER

Q8 Next, I am going to read you two statements, please tell me to what extent you agree or disagree with each of them.

I trust the federal government to set the same standards that I would set in limiting the amount of pesticide residues allowed in food.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q9 I trust that once the federal standards are set, all the food I buy will meet those standards.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q10 Now suppose that all foods met the federal standard for pesticide residues [were produced without pesticides]. What percent do you think that would reduce the chances of a health problem happening someday to people who currently do nothing to reduce or avoid pesticide residues in food?

<0-100> ENTER EXACT PERCENT

<998> DON'T KNOW/NO OPINION
<999> REFUSED/NO ANSWER

Q11 Suppose foods were tested and certified to meet federal standards for pesticide residues [to have been produced without pesticides]. Which of the following organizations do you feel would be the most effective in conducting the tests and issuing certificates?

Would you say the federal government, the state government, a well known consumer's group, or some other organization?

<1> FEDERAL GOVERNMENT
<2> STATE GOVERNMENT
<3> A WELL KNOWN CONSUMER'S GROUP
<4> SOME OTHER ORGANIZATION:SPECIFY

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q12 Suppose the federal government did the testing and certifying. How effective do you think such a program would be in ensuring that foods had no pesticide residues above federal standards?

Would you say very effective, somewhat effective, somewhat ineffective, or totally ineffective?

<1> VERY EFFECTIVE
<2> SOMEWHAT EFFECTIVE
<3> SOMEWHAT INEFFECTIVE
<4> TOTALLY INEFFECTIVE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

[Note: half the sample received question 10, 11, and 12 with "foods were produced without pesticides" replacing "foods met federal standards."]

Q13 Suppose someone from a household like yours had a health problem someday that resulted from the current levels of pesticide residues in food. In your opinion, what would the health problem most likely be? (open-ended, field coded)

Q14a Next I would like to ask a few questions about where you get your information about the health risks of pesticide residues.

In the past 6 months have you gotten information about the health risks of pesticide residues from a television program?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q14b In the past 6 months have you gotten information about the health risks of pesticide residues from your doctor or health specialist?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q14c In the past 6 months have you gotten information about the health risks of pesticide residues from an article in a magazine?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q14d In the past 6 months have you gotten information about the health risks of pesticide residues from a newspaper?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q14e In the past 6 months have you gotten information about the health risks of pesticide residues from a health newsletter?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q14f In the past 6 months have you gotten information about the health risks of pesticide residues from a radio program?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q14g In the past 6 months have you gotten information about the health risks of pesticide residues from family, relatives, or friends?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q14h In the past 6 months have you gotten information about the health risks of pesticide residues) from any other sources? (open ended, field coded)

<1> YES: SPECIFY

Q15 Next, I am going to read you several statements. In these statements, the term 'plants and animals' refers to plants and animals produced for food. Please tell me to what extent you agree or disagree with each of them.

If plants and animals were not protected in any way from insects, diseases, or other pests, the supply of food available to me would decrease.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q16 If plants and animals were not protected in any way from insects, diseases, or other pests, the food available to me would not look as good as it does now.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q17 If plants and animals were not protected in any way from insects, diseases, or other pests, the price of food available to me would increase.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q18 There are many equally effective ways other than using pesticides to protect plants and animals from insects, diseases, or other pests.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q19 It is more expensive to use other ways of protecting plants and animals from pests than it is to use pesticides.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q20 The scientific community can be trusted to be truthful about what they know about health risks from pesticide residues.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q21 The health risks associated with current levels of pesticide residues in food are well known and understood by the scientific community.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q21a Food labeled as organic means the food is grown without pesticides.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?)

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q21b All food that is labeled as organic has been certified by a reputable laboratory to have been organically grown.

Would you say you strongly agree, somewhat agree, somewhat disagree, or strongly disagree?

<1> STRONGLY AGREE
<2> SOMEWHAT AGREE
<3> SOMEWHAT DISAGREE
<4> STRONGLY DISAGREE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q22 The next few questions are about your food shopping routine.

How often is the grocery shopping done in your household? (open ended, field coded)

Q23 In the past year, has your household bought any fresh apples?

<1> YES
<5> NO

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q23a When you buy fresh apples, do you usually buy them individually, by the pound, by the bag, by the peck, or by the bushel? (open ended, field coded)

<1> INDIVIDUAL
<2> POUNDS
<3> BAGS
<4> PECK
<5> BUSHEL

<0> OTHER (SPECIFY)
<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q23b How many individual apples or pounds are usually in a bag?

<1-997>

<998> DON'T KNOW/NO OPINION
<999> REFUSED/NO ANSWER

Q24 About how often does your household buy fresh apples in the fall? (open ended, field coded)

Q24a When you buy fresh apples in the fall, on average, how many apples do you buy each time?

<0-997>

<998> DON'T KNOW/NO OPINION

<999> REFUSED/NO ANSWER

[Note: Q24 and Q24a were asked with "winter," "spring," and "summer" replacing fall.]

Q28 Now, suppose it is next fall and you are planning to buy some fresh apples. The quality of all fresh apples is what you normally expect. Apples sold loose and prepackaged are all the same price per pound. The prices of all fresh fruits other than apples are what you normally expect.

How many apples of your usual variety would you buy if all fresh apples were _ ___ (blank filled with one of several prices) per pound?

Q29 Now suppose you could also buy apples of your usual variety that have been tested and certified by the federal government to have no pesticide residues above federal standards [to have been produced without pesticides]. Fresh fruits other than apples are not certified. The certified apples are ______ per pound compared to ______ (blanks filled with one of several price combinations) per pound for the regular apples.

Would you buy certified apples, regular apples, some of both, or none at all?

<1> REGULAR APPLES
<2> CERTIFIED APPLES
<3> SOME OF BOTH
<4> NONE AT ALL

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q29a How many of the certified apples would you buy _____ (blank filled with one of many prices) per pound?

<0-997>

<998> DON'T KNOW/NO OPINION
<999> REFUSED/NO

Q29c How many of the regular apples would you buy _____ (blank filled with one of several prices) a pound?

[Note: Split sample variation of Q29, Q29a, and Q29c: "tested and certified to have been produced without pesticides.]

Q31 The last few questions are for statistical purposes only. We need the information to compare your opinions with the other households we are interviewing across Michigan.

How many people in your household are under 5 years of age?

<0-97>

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q31a How many people in your household are between 5 and 18 years of age?

<0-97>

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q31b (Including yourself), how many people in your household are between 19 and 64 years of age?

<0-97>

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q31c (Including yourself), how many people in your household are over 64 years of age?

<0-97>

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q32 Respondent's gender:

<1> MALE
<5> FEMALE

<8> DON'T KNOW/NO OPINION
<9> REFUSED/NO ANSWER

Q33 What is your age?

<18-100>

<998> DON'T KNOW/NO OPINION
<999> REFUSED/NO ANSWER

Q34 What is the highest grade of school you have completed?

<0> GRADE SCHOOL ONLY
<1> DID NOT FINISH HIGH SCHOOL
<2> HIGH SCHOOL OR GED
<3> VOCATIONAL OR TECHNICAL SCHOOL
<4> SOME COLLEGE
<5> COLLEGE GRADUATE (BA, BS)
<6> SOME GRADUATE OR PROFESSIONAL SCHOOL
<7> GRADUATE DEGREE (PHD, MD, MA, MBA)

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q35 To get a picture of people's financial situations, we need to know the general range of incomes of all respondents we interview. Now, thinking about your household's total annual income before taxes from all sources (including your job) in 1991, did your household receive $45,000 or more in 1991?

<0-7>
<3> NO
<4> YES

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q35a Was it $30,000 or more?

<3> YES
<2> NO

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q35b Was it $20,000 or more?

<2> YES
<1> NO

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q35c Was it $10,000 or more?

<1> YES
<0> NO

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q35d Was it $50,000 or more?

<5> YES
<4> NO

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q35e Was it $60,000 or more?
<6> YES
<5> NO

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

Q35f Was it $70,000 or more?

<7> YES
<6> NO

<98> DON'T KNOW/NO OPINION
<99> REFUSED/NO ANSWER

APPENDIX 5-2: PROBIT RESULTS WITH DUMMY VARIABLE "CERT"

Table A5-1: PROBIT Results with Dummy Variable "CERT"

	MODEL 1	MODEL 2	MODEL 3
Dep Var:	Z	Z	Z
Variable	**Coefficient (standard error)**	**Coefficient (standard error)**	**Coefficient (standard error)**
α_o	0.22 (0.51)	0.15 (0.51)	0.21 (0.51)
p_r	2.28*** (0.60)	2.19*** (0.60)	2.07*** (0.60)
p_c	-2.66*** (0.54)	-2.62*** (0.54)	-2.45*** (0.53)
SCHOOL	0.06** (0.03)	0.06** (0.03)	0.06** (0.03)
INCOME	0.00001** (0.000003)	0.00001** (0.000003)	0.00001** (0.000003)
UND18	0.42*** (0.12)	0.40*** (0.12)	0.39*** (0.12)
π^r	0.31 (0.26)	0.29 (0.26)	
π^r(NCVU)			-0.42** (0.21)
π^r(VLCT)			0.12 (0.15)
$\Delta\pi$(%)	0.52** (0.23)	0.54** (0.23)	0.48** (0.23)
$\Delta\pi$(%OWN)	-0.54** (0.24)	-0.48** (0.24)	-0.43* (0.24)
ϵ^r(SURE)	0.04 (0.13)		
ϵ^r(QUAL)			-0.24* (0.14)
ϵ^r(NTRSTSTD)		0.18 (0.12)	
CERT	-0.005 (0.12)	0.013 (0.12)	0.04 (0.12)
% of buying HHs	72%	72%	73%
Log (L)	-291.06	-290.96	-295.83
Pseudo R^2	.10	.10	.10
% correct predictions	74	74	74

* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

Note: Model 3 uses π^r(SUSL) as the base and π^r(NCVU) (dummy variabe that has a value of one if respondent answered "no chance" or "very unlikely" to Q2) as an explanatory variable. The models in the text use π^r(NCVU) as the base. This does not change the insignificance of the variable CERT.

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