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Applications of Decision Theory and the Measurement of Attitudes Towards Risk in Farm Management Research in Industrialized and Third World Settings

by

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APPLICATIONS OF DECISION THEORY AND THE MEASUREMENT OF ATTITUDES TOWARDS RISK IN FARM MANAGEMENT RESEARCH IN INDUSTRIALIZED AND THIRD WORLD SETTINGS*

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Beverly Fleisher and Lindon J. Robison**

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I. INTRODUCTION

In a world which conforms to the assumptions of neoclassical economics, where every decision is made with perfect knowledge and more is always preferred to less, it is a simple matter to predict and prescribe decision making behavior. But once we relax these assumptions and introduce uncertainty with respect to the outcomes of action choices, decision makers' behavior cannot be predicted without some knowledge of their subjective perception of the distribution of outcomes from available action choices, attitudes towards risk and preference for additional income.

An understanding of decision making behavior under uncertainty can aid us in several arenas. Although many decisions are made by those who are directly affected by them, other important ones are not. Policy makers are often called upon to make decisions which affect large numbers of individuals. Knowledge of the risk attitudes of the target population and how they make decisions regarding risky events can be valuable information both in policy design and program implementation. Often computer simulation models are used to generate thousands of action choices which a single decision maker could not possibly subjectively evaluate. Having a decision criterion to use in reducing the choice set to be presented to the decision maker would be extremely helpful. Finally, the study of decision making behavior under uncertainty can provide information with which to improve decision making skills.

There is a considerable debate about how people make decisions under uncertainty, what factors influence the formation of attitudes towards risk and their effect on behavior. Although many hypotheses have been set forth, few have been adequately tested; attempts to transfer theory into practice have yielded neither consistent nor reliable results nor total support or refutation of the theories or measurement methods employed.

The purpose of this report is not to resolve all of the issues raised in the debate or to provide a primer of methods.[1/] Instead, it is an attempt to carefully examine the strengths and weaknesses of the state of the art in decision theory and the measurement of attitudes towards risk in order to understand the implications which can justifiably be drawn from the past twenty years' accumulation of empirical studies in this area. This evaluation requires that we first examine the assumptions upon which the studies are based and the limitations of the methods used. Therefore, Chapter 2 presents models commonly used to predict decision makers' behavior under uncertainty.

Chapter 3 discusses the methods commonly used to obtain a measurement of attitudes towards risk. Because many of the measures of attitudes towards risk and other methods of predicting decision making behavior under uncertainty rely on the existence of a cardinal utility function for the decision maker, Chapter 4 reviews the advantages and disadvantages of different methods of deriving utility functions and the influence of the functional form of the utility function on attributed risk attitudes and predicted behavior.

The basic tools of decision theory have been used in many different types of studies of attitudes towards risk and decision making behavior. We can classify the studies conducted in agricultural settings into three general types: measurement of attitudes towards risk within the context of the expected utility model, identification of an optimal action choice given an assumed decision rule, and correlation of risk attitudes with socioeconomic variables. Each of these applications is examined in turn, beginning with empirical measurement of attitudes towards risk in Chapter 5. Chapter 6 reviews several studies which identify an optimal action choice (farm plan) for decision makers using constrained linear and other mathematical programming models which assume that the farmer is employing one of the various multiple objective decision rules discussed in Chapter 2. Many of these studies also examine the importance of risk in formulating farm plans. Chapter 7 looks at several studies which have correlated measured attitudes towards risk with socioeconomic variables. These studies have been undertaken in the hope that, if the correlations are high enough,

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[1/]Although decision theorists can be found in all of the social and behavior sciences, systems science, and electrical engineering, this report primarily draws upon the recent applied work of economists and agricultural economists. While references are made to related work in other disciplines, comparable coverage of these areas would extend far beyond the intended scope of this report and the skills of the authors.

farmers can be classified by risk attitude using more visible proxy variables such as years of schooling or age.

Farmers' attitudes towards risk are often determined for use in current and future personal policy decisions. Chapter 8 points out the major limitations which prevent the results of the studies reviewed in Chapters 5, 6, and 7 from being justifiably used for these purposes. To do so, the chapter presents arguments from the increasing body of evidence which calls into question assumptions regarding the stability of preference over time, income, and situation, and our ability to rank individuals according to their derived risk attitude coefficients. If these assumptions are not warranted, then it is not reasonable to expect that long-term generalizations or global comparisons can be made from what are essentially local, time and place specific measurements. The concluding chapter synthesizes what has been learned from thirty years of empirical work and suggests directions for future research.

Before turning to the exploration of these issues, it may be useful to review some of the basic concepts and definitions comonly used in decision theory.

Some Basic Concepts and Definitions

Most of us already have our own everyday definitions of words such as risk, uncertainty, attitudes towards risk, and probability. But in decision theory, as in other sciences, the definitions of commonly used words must be refined and formalized if they are to be operationalized and used in the deduction of theories and hypothesis and in the description of events. Therefore, this digression will be useful in giving us a common understanding of the meaning of terms which will be used throughout the remainder of the report.

Certainty, Uncertainty, and Riskiness

Certain and uncertain are adjectives used to describe events. Events with only one possible outcome are defined as certain; the single outcome has a probability of one of occurring. Uncertain events are those with more than one possible outcome; each possible outcome has a probability between zero and one of occurring. Since events are either certain or uncertain we cannot say that one event is more or less uncertain than another. Each event is either uncertain or certain.

A class of uncertain events which alter the well-being of either a well defined class of decision makers or a single decision maker are called risky events. Riskiness, because it depends on the decision makers' attitudes, likes and dislikes, cannot be made more precise without first defining whose well-being is used to give meaning to the concept. Once we define the class of decision makers, we may be able to make comparative statements like action choice A's events are more or less risky than B's. The important point to remember is that an event's riskiness depends on the preference of an individual or a class of individual decision makers. Riskiness cannot and should not be used interchangeably with the word uncertainty. Riskiness should also not be confused with the dictionary definition of the noun 'risk.' Risk is defined in the dictionary as the possibility of loss or injury. In the context of decision analysis, however, a risky event may result in favorable or unfavorable consequences for the decision maker.

These definitions of risk and uncertainty differ markedly from those proposed by Knight. In his seminal work, Risk, Uncertainty and Profit, Knight distinguished between risk and uncertainty on the basis of the amount of information available about the likelihood of outcomes of action choices. More specifically, his distinction between the two was based on the characteristics of the situation which would, or would not, allow the use of general principles or empirical information to generate probabilities. If the situation was similar to others which had occurred in the past and information about the outcomes of previous action choices could be used in the formation of a probability density function for the outcome of an action choice in the present situation, then the situation was risky. However, if the situation was unique, so that no information was available from similar situations in the past to use in formation of probabilities, the situation was uncertain. Knight associated objective probabilities with risk and subjective probabilities with uncertainty. Objective probabilities, according to Knight, were generated from empirical observations or based on general principles while subjective probabilities, which he saw as not true probabilities, were ratios of perceived likelihoods.

Many decision theorists still use Knight's definitions. For example, Roumasset, in his introduction to the proceedings of the Agricultural Development Council-CIMMYT conference on risk, uncertainty and agricultural development states that "In modern decision theory, uncertainty is a state of mind in which the individual perceives alternative outcomes to a particular action. Risk, on the other hand, has to do with the degree of uncertainty in a given situation." Other economists' despair in defining risk and uncertainty is exemplified in Stiglitz's comment, "Risk is like love; we have a good idea of what it is, but we can't define it precisely."

Definitions, of course, are neither right nor wrong. But they should be clear and understood. Unfortunately, Knight's distinction between risk and uncertainty based on kinds of information is neither. Since all information is subjectively perceived, measured, and interpreted, to base definitions on its quality is to build a definition on concepts without correspondence of our experience. In fact, not only should we refuse to accept Knight's distinction between risk and uncertainty, we should also refuse to differentiate probabilities as either subjective or objective.

Probability Measures

We assert that all probability measures are subjective. (For other views on probability, see Schoemaker.) Use of the term 'objective probability' may be misleading as all measures of probability involve a degree of subjective judgement and none can be objectively ascertained with certainty. Even when presented with the same information regarding past events, individuals will tend to interpret it in different ways, just as information from all of our senses is filtered and interpreted by the brain and can be altered depending on our physical condition and previous experience. Therefore, when the term 'objective probability' is used it should be interpreted as either the probability presented in a given gamble or the probability within some subjectively set confidence interval that an event will occur, and not as the empirically 'proven' or analytically 'true' probability.

Attitudes Towards Risk and Preference for Income

Traditionally, we have thought that the bending of the utility function could be used to measure individuals' attitudes towards risk or chance taking. This assumption was disturbing to many researchers who saw that the utility measure was taken over wealth and did not include risk or chance taking as an argument. Given this situation, they asked, "How can the utility function measure anything but preference for income?" The response of many was that the utility function measured attitudes towards risk as well as preference for income because of the methods which were used to derive individual's utility functions. (To be discussed in some detail in Chapter 4.)

During the past five years, research has been conducted which promises to resolve this debate. Mathematical psychologists and others interested in decision making behavior have developed the concept of the utility function as a composite function which combines an individual's preference for income in a riskless situation and an individual's attitude towards risk or chance taking.

In the composite utility function which we commonly use, we have no way to determine if the shape of the utility function is due to preference for income or attitude towards risk. Methods have been developed, however, which will allow one to determine an individual's preference for income in a riskless situation. This utility function for income can be compared to the composite utility function derived using standard methods to determine the relative influences of preference for income and attitude towards risk on the shape of the utility function. The important point to remember is that the utility function we commonly use is a representation of the composite of two functions, preference for income and attitude towards risk.

The Decision Problem

For a decision problem to exist, the decision maker must have more than one action choice available to him. The decision problem can be conceived of as the selection of an action choice from among a set available to the decision maker noted as a_j $(j=1, \ldots, n)$. The outcomes which may result from an action choice depend on unknown or random states of nature denoted as S_i $(i=1, \ldots, m)$ to which the decision maker assigns probability measures $g(S_i)$ $(i=1, \ldots, m)$. The final outcome resulting from the decision maker's action choice and the possible states of nature is described as O_{ij} $(i=1, \ldots, m; j=1, \ldots, n)$. O_{ij} is therefore the outcome resulting from the occurrence of the i-th state of nature given the decision maker's choice of the j-th action. The elementary outcomes O_{ij} may be in nonhomogeneous units. For example, O_{i1} may be in yields of soybeans per hectare, while O_{in} may be in cwt of milk. Because of the nonhomogeneity of possible outcomes from different action choices, the outcomes are commonly stated in terms of their cash value equivalent, y.

Table 1.1 illustrates the decision environment just described. The first column lists the possible states of nature while the second shows the decision maker's subjective assessment of the probability of each state's occurrence. The next n columns designate the action choices available to the decision maker. The outcomes y_{ij} in the body of the table indicate the interaction between an action choice and the occurrence of a state of nature.

If the outcome of each action choice is known with certainty, e.g., $g(S_1)=1$ and $g(S_i)$, $(i=2, \ldots, m)=0$, then the decision problem is a simple one. The decision maker's selection from among the available action choices depends solely upon the magnitude of the outcomes y_{ij} $(i=1, j=1, \ldots, n)$ with the largest outcome being preferred. In this case the value of y serves as an index which can

TABLE 1.1

Tabular Description of a Decision Environment

States of Nature	Probability of States of Nature Occurring	Action Choice a_1	a_i	a_j	a_n
S_1	$g(S_1)$	y_{11}	y_{1i}	y_{1j}	y_{1n}
.	.	.	.	.	.
.	.	.	.	.	.
S_i	$g(S_i)$	y_{i1}	y_{ii}	y_{ij}	y_{in}
.	.	.	.	.	.
.	.	.	.	.	.
S_m	$g(S_m)$	y_{m1}	y_{mi}	y_{mj}	y_{mn}

be used to infer preference ordering. The values of outcomes could be transformed by any function such as U to create a new index. The preference ordering would be unaffected as long as the function U is a monotonically increasing function of y. As a result, under conditions of certainty it makes little difference whether the decision maker maximizes the function U(y) (the utility of income) or y (income). The traditional approach of static production economics which assumes perfect knowledge, and hence certainty, has been to ignore the function U(y) and maximize over y.

When uncertainty as to the state of nature which may occur is introduced, the decision problem becomes more complicated because of the multiplicity of outcomes which may occur with probability greater than zero. When events are uncertain there is only one case in which the action choice is obvious. This occurs when, no matter what the state of nature, the outcomes from one action choice are always greater than the outcome from all other action choices. This case, known as first degree stochastic dominance, is extremely rare.

Ordering of action choices with uncertain outcomes requires the use of a decision rule which incorporates the preferences of the decision makers. It can be expected that the ordering of action choices will vary between individuals and also will depend, in part, on their attitudes towards risk.

II. MODELS OF DECISION MAKING UNDER UNCERTAINTY[1/]

Several approaches to indexing action choices and modeling decision making behavior under uncertainty have been suggested. The most commonly employed models fall into two general categories: decision rules which assume that the decision maker maximizes a single objective such as utility, and those which assume that the decision maker maximizes more than one objective, or maximizes that objective subject to certain constraints. Although both types of models have been applied in a wide variety of settings, neither has been subjected to rigorous empirical testing.

Safety-First Models

This section is concerned with a basic set of decision rules known as the minimax and maximax criteria, safety-first criteria, and lexicographic ordering. All of these decision rules share the assumption that the decision maker is concerned with more than one aspect of the outcome of his action choice.

With very few exceptions, these decision rules have not been adequately tested. Instead, their applications have focused on the question of whether or not attitudes towards risk affect the action choices selected by farmers within a safety-first framework.

Maximax and Minimax Rules

The maximax and minimax indexing rules describe the extremes of response to uncertainty. The maximax rule, which considers only the most favorable outcome of each action choice while ignoring all other possibilities, reflects extreme optimism. In contrast, the minimax rule, which orders action choices on the basis of only the least favorable outcome of each, reflects pure pessimism.

The maximax rule uses as an index the maximum outcome which occurs under each action choice. Using this rule, each action choice is first searched to find the most favorable outcome. Then the best of the set of most favorable outcomes is selected and its associated action choice is considered to be the one which is preferred. Suppose that the decision maker was faced with the decision problem described in Table 1.1 and that the most favorable outcomes for action choices a_i and a_j were y_{1i} and y_{1j} respectively. The values of y_{1i} and j_{1j} become

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[1/] Researchers interested in a more advanced discussion of the topics presented in this chapter are referred to Robison and Fleisher, "Decision Analysis in Agricultural Settings: An Introduction."

the index values for their associated action choices and are used to indicate preference. If $y_{1j} > y_{1i}$, the j-th action choice would be preferred over the i-th action choice by the decision maker.

In contrast to the maximax rule, the minimax rule uses the worst possible outcome of each action choice as the index value of that action. Suppose that given the decision problem presented in Table 1.1 the worst possible outcomes of a_i and a_j were y_{mi} and y_{mj}. The decision maker would prefer the best of these "worst possible" outcomes. Therefore if $y_{mj} > y_{mi}$, the j-th action choice would be preferred.

The mixed strategy model attempts to find an intermediate point between extreme optimism and extreme pessimism from which to develop an index for action choices. This method identifies both the most favorable outcomes, $y_{max,i}$ and $y_{max,j}$, and the least favorable outcomes $y_{min,i}$ and $y_{min,j}$ from the i-th and j-th action choices. Using α , a coefficient for each action choice, a linear combination is formed equal to:

$$\alpha y_{max,i} + (1-\alpha)_{min,i} = y_i^*$$

$$\alpha y_{max,j} + (1-\alpha)_{min,j} = y_j^*$$

where y_i^* and y_j^* become the preference indices for the action choices. This rule can only become operationalized if the decision maker can identify the coefficient α.

Two of the major criticisms of these models are that they ignore all values between y_{min} and y_{max} and that they do not consider the probabilities associated with each outcome of an action choice. In response to the latter criticism proponents of these rules have argued that when no data are available from which subjective probability density functions can be formed, the decision maker has no basis from which to infer anything about the distribution beyond its upper and lower bounds. But if no data except the highest and lowest values of the distribution are available, then each data point in between should be weighted equally. This results in a uniform probability density function as shown in Figure 2.1. As a result the models bear little relation to reality and have extremely limited practical relevance.

Safety-First Models

The safety-first or focus-loss model improves upon earlier models by focusing on an outcome y_d which may be different than either the most favorable or

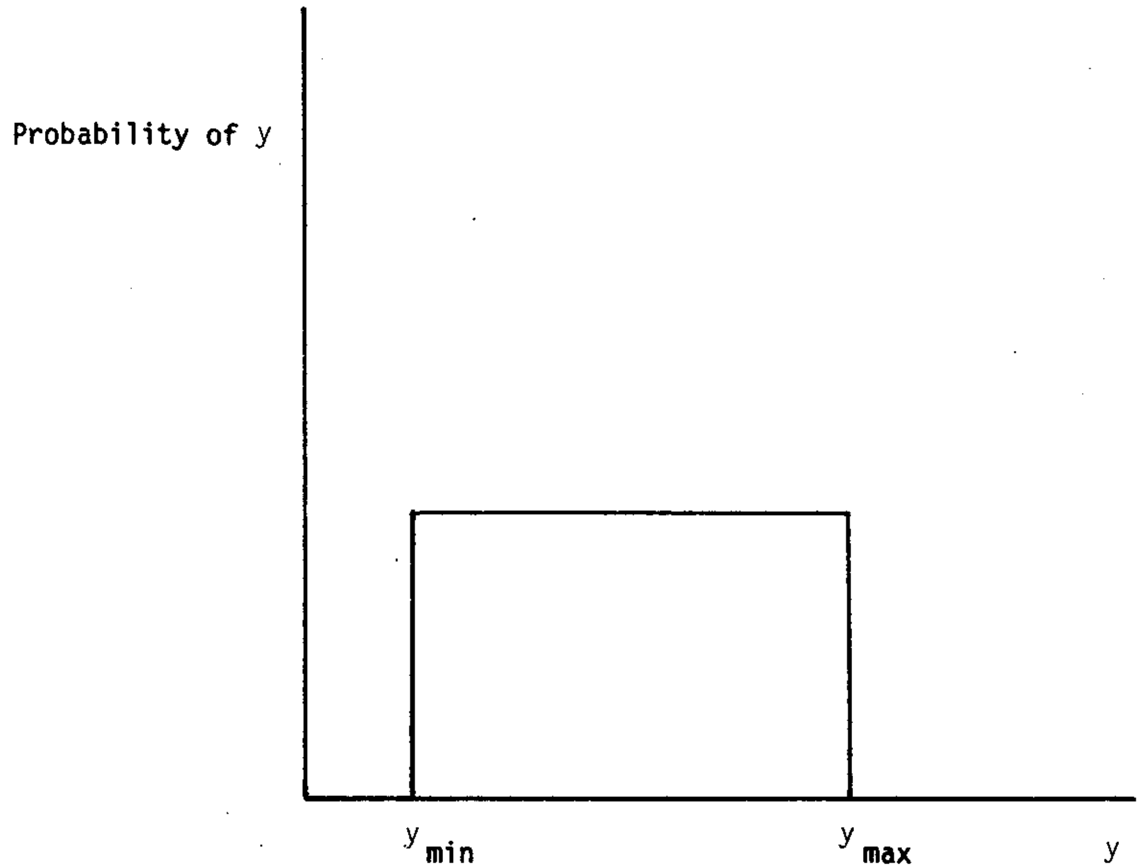

FIGURE 2.1

A Uniform Probability Density Function in Which Each Outcome Between the Maximum y_{max} and the Minimum y_{min} is Equally Likely worst possible outcome of each action choice. This outcome of concern, y_d, is often referred to as the safety or disaster level of outcome below which a firm fails to meet its cash obligation or becomes bankrupt. In a developing country context the disaster level is interpreted as the minimum level of production yields or returns needed to meet subsistence requirements. Whatever the interpretation of y_d, this model assumes that the decision maker's primary goal is to select action choices so as to minimize the chances of experiencing outcomes at or below the disaster level, y_d.

Roy suggested that investors have in mind some disaster level of returns, y_d, and that they behave so as to minimize the probability, P, of returns, y_i, below that level. Later safety-first models proposed by Telsar and Kataoka incorporated a recognition of the objective of maximizing returns or income subject to the constraint of minimizing the chances of receiving returns less than y_d.

The three alternative specifications of safety-first criterion can be stated as:

1. minimize $P(y_i \quad y_d) \leq$ (Roy)
2. maximize $E(a_i)$ subject to $P(y_i \leq y_d)$ (Telsar)
3. maximize y subject to $P(y_i \leq y_d)$ (Kataoka)

where y_i is the level of returns, y_d is the disaster level, α is the probability of disaster, and $E(a_i)$ is the expected profit of the i-th action choice.

The general concept of the safety-first models can be illustrated through the use of Figure 2.2, which shows the cumulative density functions of the outcomes of two action choices a_i and a_j. A cumulative density function for each action choice can be obtained by summing its probability density function. Point B on the cumulative density function $G_j(y)$ can be interpreted as the probability of outcomes equal to or less than $y_{b,j}$. The maximum value of $G_j(y)$ can take on is one, which is the sum of all probabilities of $y_{k,i}$ occurring.

If the decision maker acted in accordance with the safety-first model proposed by Roy when faced with the cumulative density functions presented in Figure 2.2, they would prefer the action choice a_j represented by $G_j(y)$. At the disaster outcome level y_d, $G_i(y_d)$ is greater than $G_j(y_d)$ indicating that the probability of y_d or something worse occurring is greater with the i-th action choice than with the j-th action choice. Thus action choice a_j would be preferred even though it has a lower maximum possible outcome ($y_{max,j} < y_{max,i}$) and a worse minimum outcome ($y_{min,j} < y_{min,i}$).

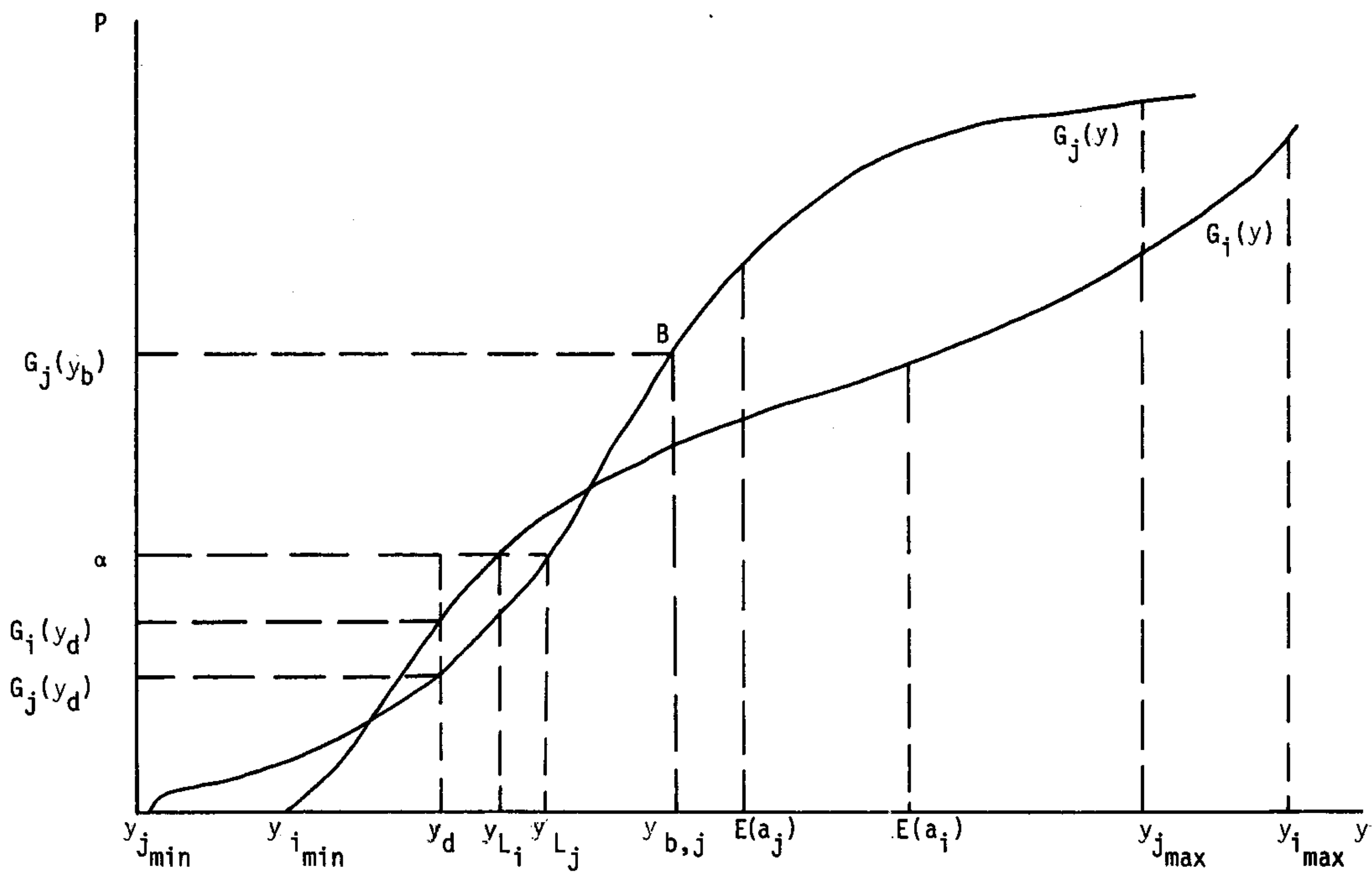

Figure 2.2. Cumulative Density Functions $G_i(y)$ and $G_j(y)$ Describing Probabilistic Outcomes of Receiving y or Something Less

If a decision maker faced with the same decision problem was using the criteria proposed by Telsar, however, he would prefer action choice a_i over action choice a_j. Under Telsar's restrictions the decision maker attempts to maximize expected returns ($E(a_k)$; $k=1,\ldots, n$), subject to the constraint that the probability of return less than the disaster outcome y_d does not exceed a given probability α. Both of the cumulative density functions in Figure 2.2 show that probability of y_d or less occurring is less than α for their respective action choices. Since this constraint is satisfied, the decision maker will base his choice on expected returns which are greater for action choice a_i than for action choice a_j ($E(a_j) < E(a_i)$).

If he follows Kataoka's safety-first rule, the decision maker would again prefer action choice a_j. This rule is based on a particular probability value of $G(y_L)$, indicated by α. The decision maker will prefer the action choice with the largest value of y_L at a given value of $G(y_L)$. In Figure 2.2 $G_j(y)$ is preferred to $G_i(y)$ since the value of $y_{L,j}$ is greater than $y_{L,i}$.

One thing which should be noted about all of the safety-first models is that they focus on only one level of outcome or one level of probability of outcomes. But should this limited view be accepted as the basis for modeling decision making under uncertainty? It would appear that if each possible outcome, y, may influence the well being of the decision maker, all possible outcomes and their attendant probabilities should be allowed to influence the preference index.

Lexicographic Ordering

All three of the safety-first models imply that the decision maker is concerned with more than one aspect of the outcome of his action choice. In safety-first models the outcomes of concern are income or wealth and the probability of receiving an outcome lower than y_d, the disaster level. A more general theory which recognizes a multiplicity of objectives is the theory of multidimensional vector ordering, or what is now more generally known as lexicographic ordering. Lexicographic ordering differs from utility analysis of a multidimensional objective function in that the trade-off weights between vectors are not measurable. Applications of lexicographic ordering to decision problems was suggested by Encarnacion and elaborated upon by Ferguson.

They propose that a decision maker has a lexicographic utility function that ranks a hierarchy of objectives $Z_1,\ldots, Z_n$ in which Z_1 is more important than Z_2, Z_2 is more important than Z_3, etc. Given two alternative action choices, Z^0 and Z^1, the decision maker will prefer Z^0 to Z^1 if $Z_1^0 > Z_1^1$, irrespective of the relationship between Z_i^0 and Z_i^1 for $i > 1$. If the two choices both satisfy the goal Z, $(Z_1^0 = Z_1^1)$, then the choice between them is based on the relative value of the second components Z_2^0 and Z_2^1. If $Z_2^0 = Z_2^1$, the choice is made with reference to the third component and so on. It is assumed that the marginal utility of overachievement of goal Z_i is zero.

One form of a lexicographic utility function in a problem of decision making under uncertainty is a function with two goals where Z_1 is a firm survival goal and Z_2 is a profit maximizing goal. Suppose that the decision maker feels that an income, I, less than $\$X_0$ is not acceptable and that he is only willing to run the risk of an income less than $\$X_0$ with a probability of .01. Goal Z_1^* is satisfied if $p(I > \$X_0) \geq .99$. Given two action choices, the decision maker will first ensure that Z_1^*, the firm survival goal, is met before expected income is maximized. Thus a distribution of outcomes with a lower expected income which satisfies Z_1^* will be preferred over one with a higher expected income which does not satisfy goal Z_1^*. The literature on lexicographic ordering does not indicate how the decision maker will respond in situations where no available action choice satisfies goal Z_1^*.

One of the most common applications of this two goal lexicographic utility approach is in focus-loss programs (Boussard and Petit) which assume that farmers want to maximize the "normal" or mean value of their incomes under the constraint that the focus of loss for the optimal corn pattern is no more than the permissible loss.

Although this simple two goal lexicographic utility function may provide the researcher with a measure of the relative levels of risk aversion present in the population (in the form of $\$X_0$ or a probability), lexicographic utility, in general, cannot be used for this purpose. This is due to the fact that goals are not always easily quantifiable and that each member of the population is likely to have different goals, or order similar goals in different ways.

The Expected Utility Hypothesis

One of the most commonly used decision rules throughout history has been the weighting of outcomes according to their monetary value and selection of the action choice with the highest expected value. This decision rule is still used today. One of its most popular applications has been in linear programming models where uncertain parameters are replaced by their expected values. The solution is then the outcome which maximizes the expected value of the uncertain parameter.

This decision rule has two advantages over safety-first and lexicograhic ordering rules: all of the outcomes which result from action choices are considered in formulating the preference index, and the preference index is unidimensional or, in other words, the decision problem is collapsed into a comparison of homogeneous units. Despite these advantages, many decision theorists argue that an expected profit maximization approach is not adequate for modeling decision making under uncertainty. Their reservations regarding this model rest upon the pioneering work of Daniel Bernoulli who showed that the degree of satisfaction which an individual derives from income is not necessarily a linear function of the amount of money.

Bernoulli's statement of the concept of diminishing marginal utility for income provided the impetus for the development of the expected utility hypothesis, which incorporates the decision maker's utility for income or wealth and his attitude towards risk into a preference ordering rule. Although the expected utility hypothesis has not been proven to be the perfect decision rule, it is the most generally accepted decision paradigm and is the basis for almost all of the disciplinary work done on the economics of uncertainty.

Bernoullian Utility Analysis

Daniel Bernoulli, an eighteenth century mathematician who studied decision making behavior, found an inconsistency between the expected value rule and the way that decision makers actually behaved. He postulated that this inconsistency arose because the satisfaction or "utility" which individuals gained from a unit of money was dependent upon more than the face value of the money. He reached this conclusion after observing two phenomena. The first was that a given small amount of money appeared to be worth more to a poor man than a rich one. The second was the inconsistency which arose when individuals played a gamble known as the St. Petersburg paradox. The gamble paid depending on the number of flips of a coin required to obtain heads. If a head occurred on the first flip, the gamble paid a small sum such as \$2. If a head occurred on the second flip the gamble paid $(\$2)^2$ or \$4, if it occurred on the third flip it paid $(\$2)^3$, and so on. The probability of heads occurring on the first flip, is 1/2, 1/4 on the second flip, and 1/8 on the third flip. The expected value of the gamble E(G) could be written as the sum:

$$E(G) = 1/2\ (\$2) + 1/4\ (\$4) + 1/8\ (\$8) + \ldots$$

The value of each element in the gamble is one. But the number of possible elements is infinitely large so that the sum, or expected value, is infinite. If decision makers played this gamble in accordance with the expected value rule they should be willing to pay a relatively large amount to play since the gamble's expected value is infinite. But Bernoulli observed that gamblers were only willing to pay a small amount to play.

Bernoulli proposed that decision makers playing the St. Petersburg paradox maximize the log function of the outcomes. This is equivalent to maximizing the geometric mean of a gamble, which will result in either maximizing the expected value of terminal wealth or minimizing the number of plays required to achieve some level of wealth in a repeated gamble (Bierman). Although it is now realized that the log function is not necessarily an appropriate or universal weighting function for income, Bernoulli's work represented a significant step towards modern decision theory.

The Expected Utility Hypothesis

Bernoulli's concept of utility of income provided the basis for the expected utility hypothesis (EUH), first formally deduced from a set of axioms by Ramsey and later developed more fully by von Neumann and Morgenstern. The EUH asserts that if a decision maker's behavior is consistent with four axioms of "rational behavior" he will weight outcomes of action choices according to a personalized and unique function $U(\Pi)$. The expected value of $U(\Pi)$ for each action choice provides the single valued index which orders action choices in accordance with the decision maker's preferences or attitudes toward risk.

The four axioms of "rational behavior" which expected utility maximizers are assumed to follow are:

1. Ordering. If an individual confronts two risky prospective action choices a_1 and a_2, each with more than one potential outcome or with a probability distribution of outcomes, he will prefer one of the two risky prospects or will be indifferent between them.

2. Transitivity. If an individual confronts three risky prospects, a_1, a_2, and a_3 and prefers a_1 to a_2, and a_2 to a_3, then he will also prefer a_1 to a_3.

3. Continuity. If an individual prefers a_1 to a_2 to a_3, then there exists a unique probability, p, such that he will be indifferent between a_2 and a lottery of the form $pa_1+(1-p)a_3$.

4. Independence. If action choice a_1 is preferred to a_2 and a_3 is some other lottery, then the individual will prefer a lottery of $pa_1+(1-p)a_3$ to the lottery $pa_2+(1-p)a_3$.

If the decision maker obeys these axioms, a utility function $U(\Pi)$ can be formulated which reflects the preferences of the decision maker (Hey). According to the expected utility hypothesis, a utility function $U(\Pi_i)$ derived for an expected utility maximizer has the following properties:

1. If a_1 is preferred to a_2 then $U(\Pi_1) > U(\Pi_2)$.

2. The utility of a risky prospect is equal to the expected utility of its possible outcomes.

3. The scale on which utility is measured is arbitrary. Therefore the utility function is unique only up to a linear transformation.

Utility functions are discussed in greater detail in Chapter 4.

The EUH assumes that individuals meet two initial conditions in addition to following the axioms of rational behavior already introduced. The initial conditions are that they can identify a set of action choices $a_1,\ldots, a_n$ and that they can associate probability density functions $g_1(\Pi),\ldots, g_n(\Pi)$ with the action choices. The probability density functions are subjective and assumed to obey the calculus of probability.

The expected utility hypothesis prescribes the following solution for an uncertain decision problem:

1. Identify the action choices as $a_1,\ldots, a_n$ and the possible states of nature $\Theta_1,\ldots, \Theta_m$ under which the action choices may be experienced.

2. Assign probability weights to the states of nature $p(\Theta_1),\ldots, p(\Theta_m)$ consistent with probability calculus.

3. Calculate the expected utility value of the consequences for each action choice.

4. Implement the action choice with the highest expected utility.

Although the safety-first criteria introduced earlier were originally developed as an alternative to the EUH, Pyle and Turnovsky have shown that some safety-first models can be deduced from the EUH. For example, in the absence of a riskless asset, a safety-first model can be inferred from expected utility maximization when that maximization results in concave indifference curves in a mean-standard deviation space. If, on the other hand, a riskless asset is available, the criteria do not produce consistent results.

Moreover, Robison and Lev have shown that apparently safety-first type behavior can be explained by EUH models once the probability distributions are adjusted for institutional constraints which limit decision makers' liabilities.

Some supporters of the EUH claim that if the decision maker selects an action choice using the procedures outlined by the EUH he will be acting in accordance with his expressed preferences. The utility function is only a device for attributing numbers or an index to possible outcomes of an uncertain prospect in order to help the decision maker select from among a set of prospects. Others argue that the EUH is a useful tool for predicting decision maker behavior whether or not they have consciously followed the procedures outlined by the EUH. Dillon makes this distinction through the analogy that catching a ball requires the intuitive solution of complex differential equations. The fact that the ball is caught does not imply that the differential equations were actually solved by the catcher, only that the catcher behaved as if he had solved the equations.

Testing The Hypotheses

According to Giere, a good test of a theoretical hypothesis requires an experiment or a set of observations which involves the hypothesis, initial conditions, auxiliary assumptions, and a prediction. For the hypothesis to be supported, two conditions must be met. The first condition is that if the hypothesis, initial conditions, and auxiliary assumptions are true, then a correct prediction will probably follow. This condition requires an experiment which involves careful identification and definition of the hypothesis, initial conditions and auxiliary assumptions and the making of a prediction. A comparison of the actual and predicted outcomes constitutes completion of test condition one. Condition one can be viewed as a test of correspondence.

The second condition for a test of a hypothesis is that if the initial conditions and auxiliary assumptions are correctly specified but the hypothesis is not true, then the probability of making a correct prediction is small. In addition, given the same initial conditions and auxiliary assumptions, an alternative hypothesis would not predict behavior as well as the one which is being tested. If the same prediction results from many alternative hypotheses, the second test condition would not be met and the theoretical hypothesis is not fully justified. Condition two is a test of clarity or lack of ambiguity.

The word 'probably' in test conditions one and two identifies the model in question as probabilistic rather than deterministic. Therefore, perfect prediction is not expected. Instead, what is required is that statistically significant evidence does not permit a rejection of the model. In summary, a good test of a theoretical hypothesis requires not only that it be able to predict an outcome, but that competing hypotheses not predict the outcome as well. Additional tests which should be carried out are the tests of consistency, that the hypothesis can be logically deduced from the assumptions, and, if one is a pragmatist, the test of workability or the usefulness of a concept in helping to attain a desired end (Johnson, 1982).

Tests of Safety-First Type Models

Most applications of the safety-first model do not meet conditions one and two of a good test of a hypothesis. Their major emphasis appears to be the determination of the importance of including risk attitude considerations in mathematical programming models designed to predict farmers' cropping choices. These applications are discussed in several of the chapters which follow and receive special consideration in Chapter 6.

Tests of the Expected Utility Hypothesis

The concepts of statistical decision theory which form the basis of the expected utility hypothesis are essentially prescriptive; they describe how a rational decision maker ought to behave given his beliefs and preferences. Whether or not they provide a model which explains rational behavior can only be determined by empirical test. After more than twenty years of experimental investigation of decision making under uncertainty, evidence regarding the predictive validity of the expected utility hypothesis is still inconclusive. Very few of the experimental applications of the expected utility model meet both conditions one and two of Giere's test of a theoretical hypothesis. These studies will be reviewed in this section. Many of the agricultural applications of the expected utility model have focused on the determination of farmer's attitudes towards risk and have not attempted to test the validity of the model. These studies will be reviewed in later chapters.

Lin, Dean, and Moore developed a test of the expected utility hypothesis which met Giere's conditions one and two. Three alternative decision criteria, expected utility maximization, profit maximization, and maximization of utility in a lexicographic context, were tested to determine how well they predicted individual producer behavior. Condition one was met as the predictions made by the expected utility hypothesis were compared to individual producer behavior. Condition two was met because the authors compared the accuracy of these results with the accuracy of alternative models.

To describe the action choices facing six farmers in California's San Joaquin Valley, the authors used quadratic programming techniques to develop an efficient choice set for each farmer. Utility functions for each farmer were developed using subjective probabilities to simulate the decision environment. This was done to avoid the bias which would be caused by the use of probability estimates derived from countywide statistics. The four goals assumed in the lexicographic model were family living standard, firm growth, net income, and farm survival.

Predictions made by each of the three models were compared to actual farm plans. The expected utility model was the most accurate in three cases while the lexicographic utility model most closely predicted the decision makers choice in two out of the remaining three cases. None of the models predicted actual behavior well; all tended to predict more risk preferring behavior than was actually observed. In fact, it would have been impossible for the expected utility hypothesis to predict the actual farm plans used by the farmers because these plans were not included in the efficient choice set. Thus an important initial condition required for the test, the correct identification of the choice set, was not met.

The test was then repeated with the model's predictions compared to the farm plan selected by the farmer from those presented. In this test the expected utility model prediction corresponded with the farmers preferred plan in three out of six cases and was more accurate than either of the competing models in the remaining three cases. These results lend support to the expected utility hypothesis.

Haneman and Farnsworth studied the ability of the expected utility maximizing and profit maximizing models to predict farmers' choices between integrated pest management (IPM) and conventional chemical control strategies. In their study, Haneman and Farnsworth estimated utility function and subjective probability estimates of prices and yields for each of the forty-four farmers. They found no significant difference in the risk attitudes of the two groups. However, they did find significant differences in the subjective expectations regarding yields and profits between the IPM and chemical control groups despite the fact that historically there was no significant difference. Each group was able to nominate subjective probability distributions for their own control strategy which were similar to the probability distributions developed using historical data. Each group, however, tended to underestimate the expected value of profits and yields which could be obtained through the use of the alternative strategy.

The authors found that the expected utility maximizing model was able to predict the farmers choice of pest control strategy in thirty-five out of the forty-four cases. Thus, condition one of the test was completed. They then found that the expected profit maximizing model also correctly predicted the farmers' preferred strategy in thirty-five out of the forty-four cases. Although the expected utility hypothesis passed condition one of a good test of a theoretical hypothesis, it failed condition two because an alternative hypothesis was shown to produce the same results. Therefore, this study provides only weak support for the expected utility hypothesis. Haneman and Farnsworth infer, however, that the subjective perceptions of outcomes rather than the type of choice criterion or the farmers' attitudes towards risk explain the choices between conventional and pest control strategies. Since no test of the models was completed using objective probability distributions, this inference still requires empirical validation.

Although the expected utility hypothesis is considered by many decision theorists to be the best available model of decision making under uncertainty, empirical tests of the model have not given it unconditional support. It has been shown that the expected utility hypothesis can predict decision makers' choices in a hypothetical setting, but its predictive ability is not clearly superior to that of competing models. The two tests discussed leave unanswered several important questions about the expected utility hypothesis such as whether decision makers actually calculate the expected utility to be obtained from each risky choice before selecting the preferred action, or whether they only act as if they do.

III. LOCAL MEASURES OF ATTITUDES TOWARDS RISK

The ability to explain, predict and prescribe behavior in risky situations is dependent upon knowledge of the individual's willingness to bear risk. While the existence of risk aversion can be used as an explanation of some economic activities, a suitable numerical measure is needed to arrive at quantifiable theories. Several measures have been developed; according to Arrow the ultimate justification for any particular measure is its usefulness in theories of specific types of behavior under uncertainty.

All of the measures of attitudes towards risk commonly used are composite measures of attitudes towards risk or chance taking and preference for riskless income.

Classification According to the Shape of the Utility Function

One method of classifying individuals' attitudes towards risk is by the shape of their utility function over wealth. It is assumed that all investors display marginal utility for additional wealth such that $U'(y) > 0$, $U''(y) < 0$; that is, their preferences are represented by an expected utility function, $U(y)$, which is monotonically increasing and twice differentiable. The concavity, convexity or linearity of the utility function reflects the decision makers attitude towards additional income with concavity indicating diminishing marginal utility (risk aversion), convexity indicating increasing marginal utility (risk preferring) and linearity reflecting constant marginal utility (risk neutrality).

Although we classify individuals as risk averse, risk preferring, and risk neutral by the shape of their utility function, we commonly cannot ascertain whether the curvature of their utility function is due to preference for income or their attitude towards risk as the utility function is a composite of the two functions.

Figure 3.1 represents the linear utility function of an individual who has constant marginal utility of income and hence, is classified as risk neutral. If this decision maker is presented with a choice between receiving a sure amount, $\bar{y}$, or participating in a gamble with a fifty percent chance of receiving y_1 and a fifty percent chance of winning y_2, with a mean value of $\bar{y}$, he will be indifferent between the two options. Because of the linearity of his utility function the expected utility to be gained from $\bar{y}$ is exactly equal to the expected utility of the gamble, which can be expressed as $EU[.5y_1 + .5y_2] = 1/2\ U(y_1) +$

$1/2\ U(y_2) = U(\bar{y})$. Similarly, if the same decision maker is presented with a third alternative, a fifty percent chance of winning y_3 and a fifty percent chance of winning y_4, which also has a mean value of $\bar{y}$, he will be indifferent between all three options. Furthermore, he will be indifferent between any gambles whose expected values are equal.

In contrast to this risk neutral decision maker whose utility function is shown in Figure 3.1 is the risk averse decision maker for which a representative utility function is shown in Figure 3.2. If presented with the same action choice as the risk neutral decision maker, the risk averse decision maker will not be indifferent between $\bar{y}$ and a gamble in the form of $1/2(y_1) + 1/2(y_2)$. The expected utility of the gamble $EU(y)$ is $1/2[U(y_1 + U(y_2)]$, which is equal to an income y_{CE} which, if received with certainty, would give the same amount of utility as the lottery. Note that for the risk averse decision maker y_{CE} is not equal to $\bar{y}$. In fact, the wider the dispersion of outcomes of the lottery, the greater will be the difference between $\bar{y}$ and y_{CE}.

This result should not be surprising if one considers also the slope of the line AB drawn tangent to the utility function (y) which indicates marginal utility. The fact that it is below the utility function indicates that the decision maker has diminishing marginal utility for additional income.

For a decision maker whose utility function shows increasing marginal utility for income or risk preferring behavior, as illustrated in Figure 3.3, the certainty equivalent for the gamble between y_1 and y_2 is greater than $\bar{y}$.

The shape of the utility function can be used to classify decision makers into three broad categories of risk loving, risk averting and risk neutral. However, this method does not have the capacity to order individuals within each category according to their attitude towards risk. To do so requires a more discriminating measure.

Ordering Individuals According to Their Required Risk Premium

One method of ordering individuals according to their attitude towards risk is to determine how they would respond to an identical gamble. Assume that there are two risk averse decision makers whose utility functions are shown in panels a and b of Figure 3.4. When presented with the choice between a sure outcome of $\bar{y}$ and the outcome of a gamble with an equal chance of receiving y_1 or y_2, both of the individuals would prefer $\bar{y}$. This information alone does not permit the ordering of individuals according to their attitudes towards risk. But ordering can be accomplished through the determination of each individual's 'risk

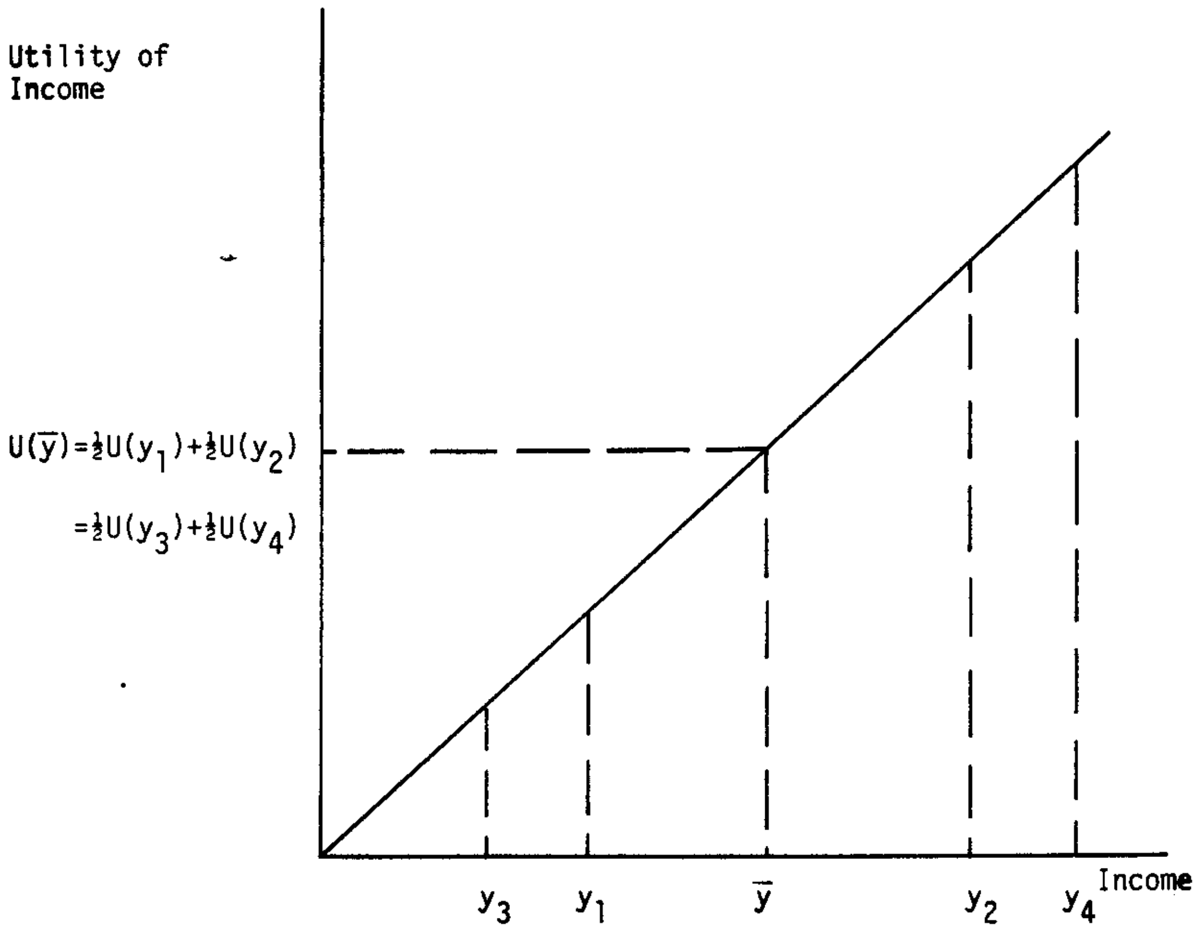

FIGURE 3.1

Linear Utility Function Displaying Constant Marginal Utility of Income

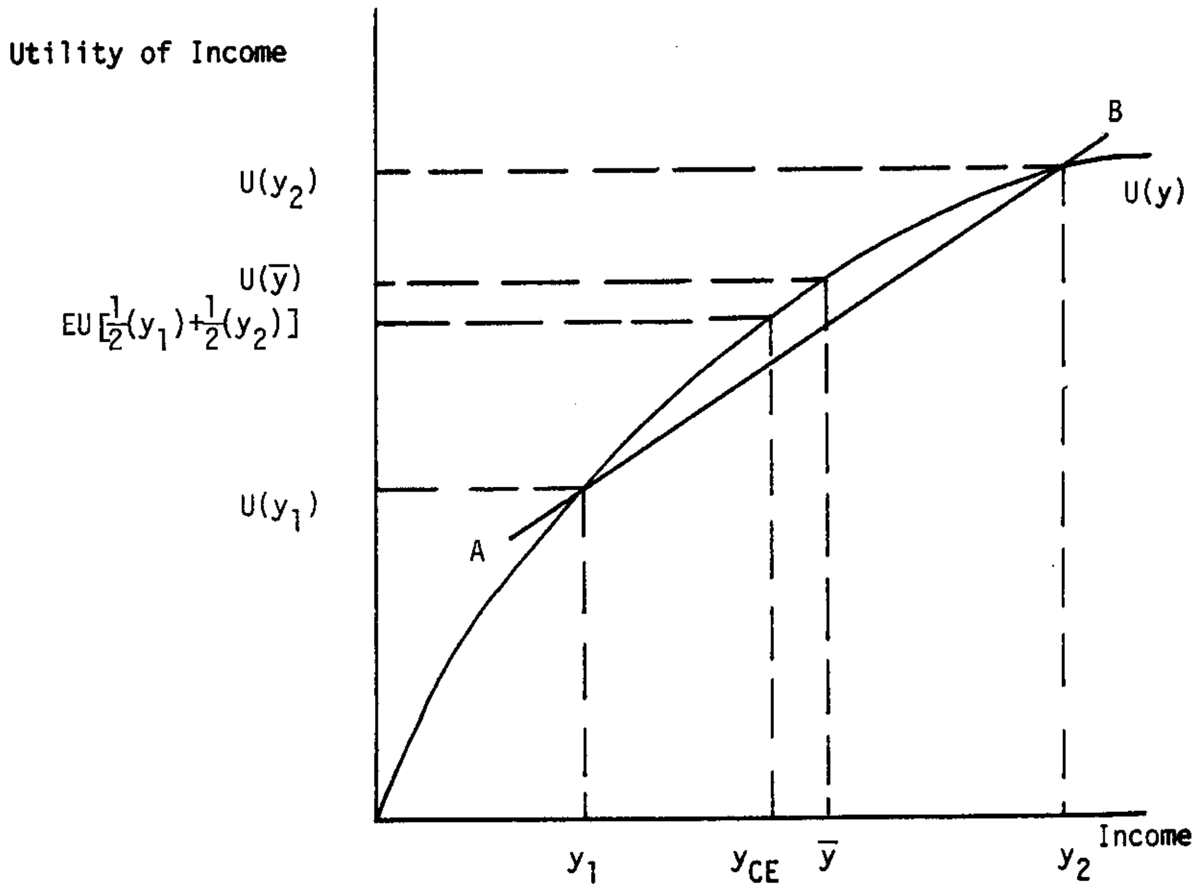

FIGURE 3.2

Concave Utility Function Displaying Decreasing Marginal Utility of Income

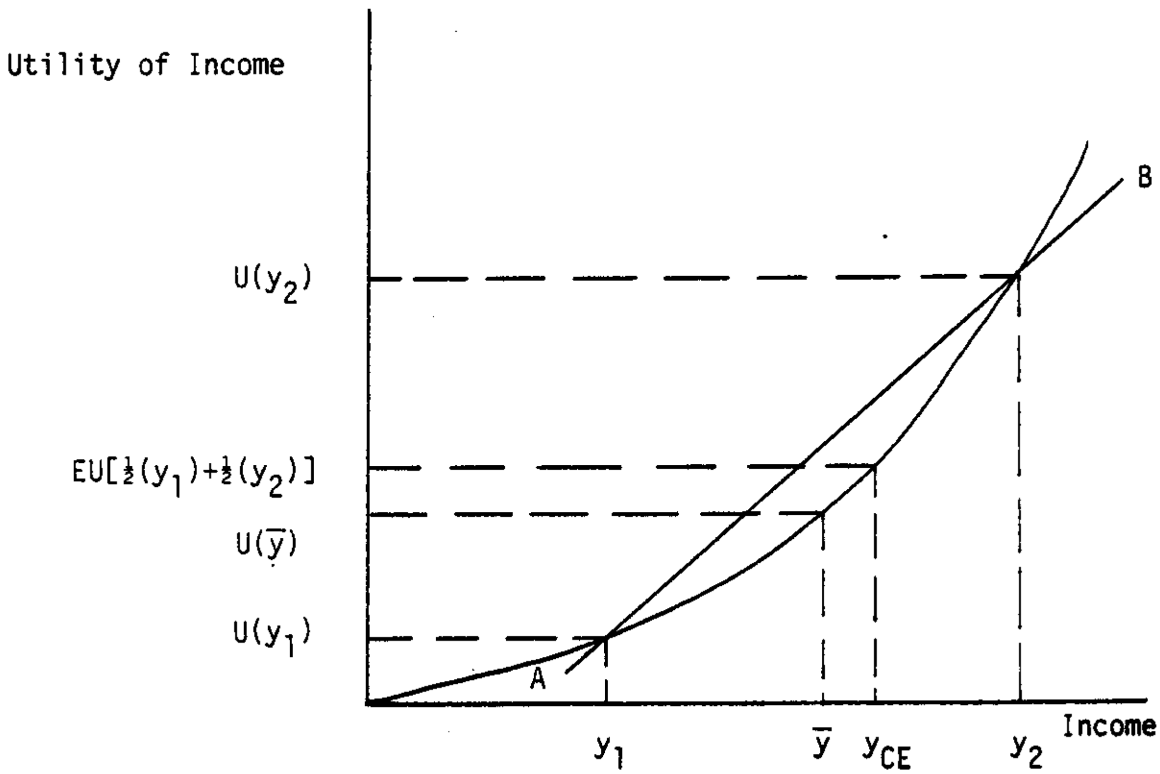

FIGURE 3.3

Convex Utility Function Displaying Increasing Marginal Utility for Income

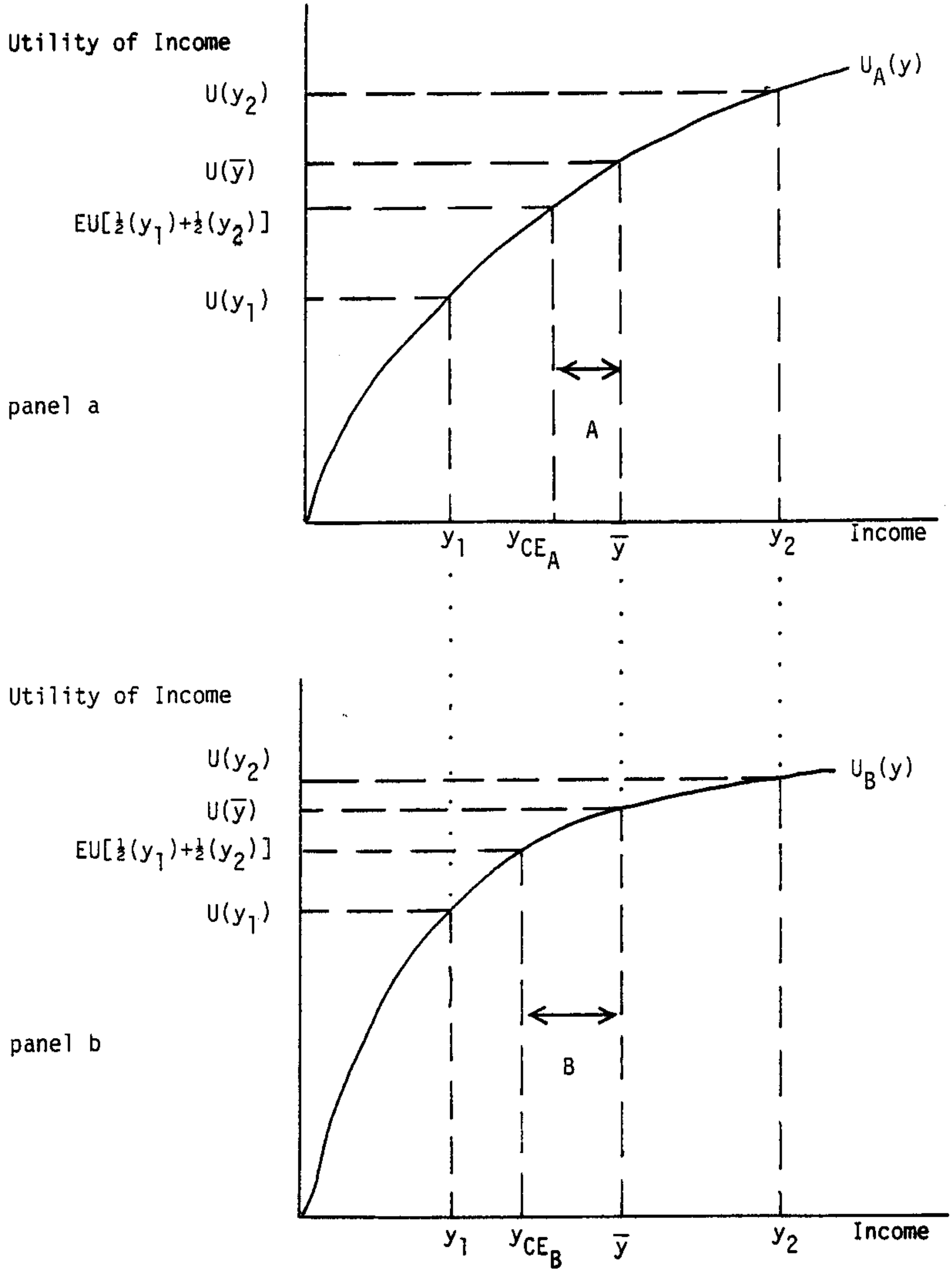

FIGURE 3.4

A Comparision of Risk Attitudes of Individuals A and B with Utility Functions $U_A(y)$ and $U_B(y)$ and Certainty Equivalent Incomes y_{CE_A} and y_{CE_B}

premium' or the difference between the expected value of the lottery, $\bar{y}$, and the individual's certainty equivalent, y_{CE}. The risk premium is usually noted by Π. Within the class of individuals who are risk averse, the larger the risk premium, the more averse to risk is the individual within that local area.

Returning to Figure 3.4 it can be seen that individual B has a larger risk premium than individual A. Hence, he is more risk averse. The size of the risk premium required is determined by the degree of concavity of the utility function, with a more concave utility function indicating a greater degree of risk aversion. On this basis the individual whose utility function is depicted in panel b of Figure 3.4 is classified as more risk averse than the individual whose utility function is shown in panel a.

As the concavity of the utility function is reduced, the risk premium approaches zero. The certainty equivalent of a risk neutral decision maker with a linear utility function equals the mean of the lottery, $\bar{y}$, and the individual requires no risk premium.

For a risk loving decision maker whose utility function is convex, the risk premium will be negative. In other words, the certainty equivalent will be greater than the mean of the lottery. The larger the absolute value of the risk lover's risk premium, the more risk preferring he is.

The shape of the utility function, concave, convex, or linear can be distinguished by the second derivative of $U(y)$. For a risk averse decision maker $U''(y) < 0$, for a risk neutral decision maker $U''(y) = 0$, while for a risk loving decision maker $U''(y) > 0$. There is no reason, however, why one individual cannot have a utility function, such as the Friedman-Savage utility function, which has a combination of convex, linear, and concave segments.

Although determining attitudes toward risk based on $U''(y)$ is appealing in its simplicity, it does have one major drawback: the risk preference indicator $U''(y)$ can be arbitrarily varied by multiplying the utility function by a positive number. Therefore, because an individual's utility function is unique only up to a linear transformation, a measure is needed which remains invariant under positive linear transformation of the utility function.

Arrow-Pratt Coefficient of Absolute and Relative Risk Aversion

Although the nonuniqueness of utility functions prevents their use as a reliable measure of attitude towards risk, the rate at which the utility function bends is unique. Arrow and Pratt independently developed two measures based on the rate of change in slope of the utility function. The first measure, known as the Arrow-Pratt coefficient of absolute risk aversion, directly measures the insistence of an individual for more than fair odds, at least when bets are small. It is defined as:

$$R(y) = \frac{-U''(y)}{U'(y)}$$

A related measure, the Arrow-Pratt coefficient of relative risk aversion, measures the elasticity of the marginal utility of wealth. It is defined as:

$$R_r(y) = \frac{-YU''(y)}{U'(y)} = \frac{-U''(y)}{U'(y)}y .$$

The Arrow-Pratt coefficient of relative risk aversion is invariant not only with respect to changes in units of utility but also with respect to changes in the units of wealth. Therefore, the absolute coefficient of risk aversion is replaced by the relative coefficient of risk aversion when the bet is measured as a proportion of wealth rather than in absolute terms. Both coefficients are positive for risk averse decision makers, zero for risk neutral decision makers, and negative for risk loving decision makers. Arrow has hypothesized that individuals exhibit decreasing absolute and increasing relative risk aversion over wealth.

Coefficient of Partial Relative Risk Aversion

Menezes and Hanson and Zeckhauser and Keeler have defined a measure of size of risk aversion, or partial relative risk aversion, as:

$$R(y,t) = \frac{-tU''(y+t)}{U'(y+t)}$$

where t is a multiplicative increase in the distribution of a risky prospect. The advantage of this measure over absolute and relative risk coefficients is that for measurement it requires only that the risk associated with an activity be changed while the wealth levels of outcomes remains constant. This may eliminate problems encountered in measuring utility over a range of wealth levels which are beyond the experience of the respondent.

Risk Aversion in the Small and in the Large

The measures of risk aversion discussed so far all rely on attributes of an individual's utility function, whether it be the general shape or its slope. It has been pointed out that these measures are commonly used to compare individuals' attitudes towards risk. Three factors prevent theorists from accepting these measures as an accurate basis upon which to rank individuals. These include the fact that it is still unclear what utility functions actually represent, the fact that the Arrow-Pratt measures and the related Zeckhauser-Keeler measure of risk aversion are point measures, and indications that risk attitude coefficients are not independent of probability measures.

No definite conclusion can be reached regarding the concern over what the utility function actually represents. U(y) is simply a function defined over income or wealth, y. The manner of its derivation, through finding points of indifference between risky alternatives, makes it unclear whether the function represents only an ordinal ranking of certain incomes or whether it is also a measure of attitudes towards risk. The ordinal utility function itself contains no element of risk or uncertainty in it. Nevertheless, it is accepted by many decision scientists as an adequate base from which to derive measures of attitudes towards risk.

In the section of this chapter on ordering individuals according to their risk premiums it was asserted that "the larger the risk premium, the more averse to risk the individual." This assertion is substantiated by Pratt who has derived an approximate relationship between the risk premium and the Arrow-Pratt measure of absolute risk aversion. The Arrow-Pratt coefficient of absolute risk aversion can be determined at any point on an individual's utility function. This arbitrary point can, for example, be specified as $\bar{y}$. Similarly, a risk premium measure of attitude towards risk can be derived from the same individual's utility function by asking "for a small gamble with variance σ^2 and mean y_m, what risk premium, Π, would the individual be willing to pay to eliminate the uncertainty?" The approximate relationship Pratt found between these two measures is that:

$$\Pi = R(\bar{y})\sigma^2/2$$

or the risk premium Π, is equal to the value of the coefficient of absolute risk aversion at $\bar{y}$ times the variance of the action choice divided by two. The certainty equivalent of the gamble can be found by replacing Π, the risk premium, with $y_{CE} - \bar{y}$. This can be expressed as:

$$y_{CE} = \bar{y} - R(\bar{y})\sigma^2/2.$$

It can thus be inferred that the more risk averse the individual, the larger the risk premium he will require, ceteris paribus. Therefore, at a point, or "in the small," individuals can be ordered according to their attitude towards risk measured in terms of a risk coefficient or a risk premium.

The important qualifier in the above statement is the phrase "at a point." Although individuals can be ordered according to attitude towards risk "in the small" through the use of the risk premium or coefficient of risk aversion, these point measures do not allow for the global ordering of individuals. As a case in point, consider the two individuals whose absolute risk aversion functions, $R_A(y)$ or $R_B(y)$ are shown in Figure 3.5. When presented with a gamble with outcomes of y_1 and y_2 and a mean of $\bar{y}*$, individual B is more risk averse than A since $R_B(\bar{y}*)$ is greater than $R_A(\bar{y}*)$. On the other hand, when presented with a gamble with outcomes y_3 and y_4 with a mean of $\bar{y}**$, individual A is determined to be more risk averse than B since $R_A(\bar{y}**)$ is greater than $R_B(\bar{y}**)$.

If the individuals are presented with a gamble whose outcomes are y_2 and y_3 with a mean of $\bar{y}$, it cannot be determined, on the basis of a local or "small" measure of risk aversion, which individual is more risk averse because the risk aversion functions cross between y_2 and y_3. Furthermore, determining the individuals' risk premiums for the gamble will not solve the quandary as many utility functions with identical absolute risk aversion functions also have identical risk premiums. In addition, by shifting the probabilitity weights between y_2 and y_3, the outcomes of the gamble, the risk averse orderings of the two individuals, based on risk premiums, can be reversed. This is inconsistent with the notion that attitudes towards risk are independent of probability measures.

This simple example is powerful in that it shows that efforts to order globally individuals according to attitudes towards risk measured "in the small" can lead to grossly inaccurate conclusions. This point should be kept in mind as the reader reviews LChapters 6 and 8 on empirical measurement of farmers attitudes towards risk and the correlations between risk attitudes and socioeconomic variables.

What conditions must be met before it can be stated that one decision maker is globally more risk averse than another? One sufficient condition is that the utility function $U^*(y)$ bends at a greater rate everywhere than does utility function $U(y)$. Pratt has demonstrated that this condition will hold if $U^*(y)$ is a concave transformation of $U(y)$.

If one decision maker is globally more risk averse than another, it can be shown that for every lottery faced by the two individuals the more risk averse will pay a larger risk premium than the other to eliminate uncertainty. In addition, the more risk averse decision maker will have a higher Arrow-Pratt coefficient of absolute risk aversion at every income or wealth level than his relatively less risk averse counterpart.

Although global ordering of individuals according to their risk aversion "in the large" is an important concept, it is rare to find two individuals which

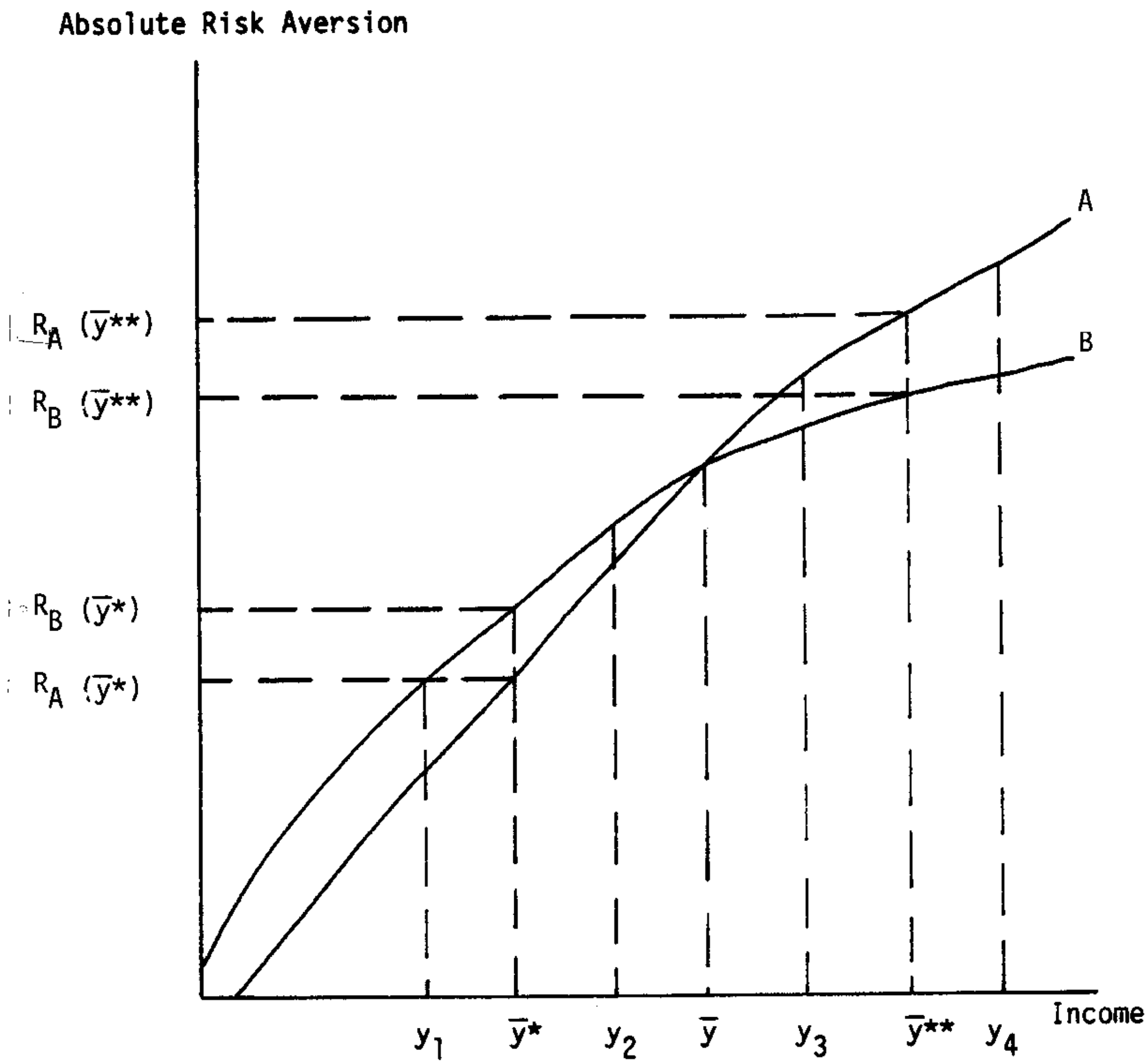

FIGURE 3.5

A Comparison of Risk Aversion Functions $R_A(y)$ and $R_B(y)$ Over Outcomes y for Individuals A and B

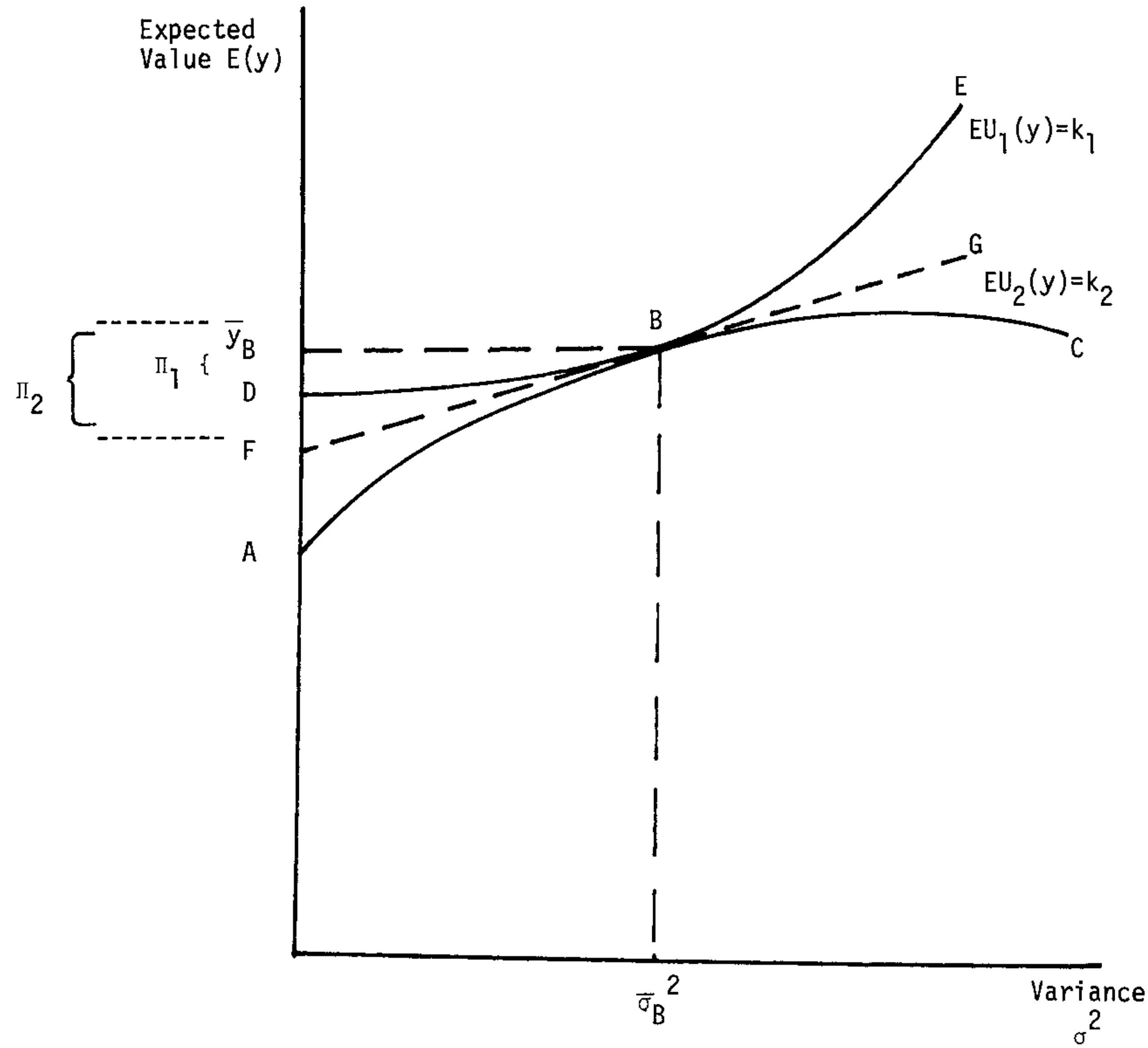

FIGURE 3.6

An Expected Value-Variance Efficient Choice Set With Isoexpected Utility Functions for Two Individuals can be ordered in this manner. This fact does not diminish the salience of the point that for distributions with dispersion beyond local bounds it is untenable to assume that individuals can be adequately ordered on the basis of local measures of attitudes towards risk.

Expected Value-Variance Trade-offs

Although not explicitly used to measure individuals' attitudes towards risk, it is common practice to infer risk attitude orderings from the choices made by individuals from within an expected value-variance (EV) efficient set. Describing the efficient choice set faced by individuals in terms of expected values and variances of the probability distributions of outcomes has been popular because quadratic programming models can be used to define an efficient set for any individual. If the individual is a risk averse expected utility maximizer and the probability distribution functions are normal, his preferred choice will always be a member of the EV set. Once the equilibrium action choice is selected, risk attitude can be inferred from the slope or trade-off between risk attitude measures "in the small" and "in the large."

Figure 3.6 illustrates an EV set. The solid line ABC represents the efficient set of action choices for the decision maker. The area below ABC includes other feasible choices which would be less preferred by all risk averse decision makers than some point on the line. These alternatives are less preferred because risk averse individuals, who have diminishing marginal utility for money, will prefer the probability distribution with the lowest variance for any given mean. Another way of defining what should be included in the efficient set is set forth by Meyer, who states that if a group of decision makers face any given set of alternatives, an efficient set for that particular group of decision makers is any subset of the alternatives which contains every alternative which would be accepted by one or more of the decision makers. Meyer argues, however, that this latter definition results in an efficient set which is larger than necessary.

The individual of concern in Figure 3.6 has selected the action choice represented in terms of mean and variance at point B as his preferred action choice. Therefore it can be assumed that action B with mean $\bar{y}_B$ and variance $\bar{\sigma}_B^2$ maximizes his expected utility at a level which will be called k. This knowledge allows for the mapping of an isoexpected utility curve for the individual which describes all action choices whose combination of means and variances results in an expected utility of k_1 for this decision maker. This isoexpected utility function is represented by the line DBE.

Individual number one may not be the only decision maker to select B as his preferred action choice. Individual number two also finds that B with a mean of y_B and variance σ_B^2 maximizes his expected utility at a value of k_2. But because individual two has a different marginal utility for money than individual one, has isoexpected utility function for k_2 is shown in Figure 3.6 as the dashed line FBG.

Ordering of individuals number one and number two by their degree of risk aversion can be accomplished by examining the slopes of their isoexpected utility lines and the risk premiums which they require. For individual one, the intercept D defines an action choice with an expected utility of k_1 which has zero variance. Therefore, D represents a certainty equivalent outcome noted as $y_{CE,1}$. The slope of his isoexpected utility line at equilibrium is adequate to $\lambda/2$. This information can be used to define the expected value of the action choice at point B as:

$$\bar{y}_B = y_{CE,1} + (\lambda \bar{\sigma}_B^2)/2$$

This can be rearranged to obtain:

$$\bar{y}_B - y_{CE,1} = (\lambda/2)\bar{\sigma}_B^2 = \Pi$$

which by definition is the risk premium. This can be measured directly from Figure 3.6 as:

$$\Pi_1 = \bar{y}_B - D$$

The slope is the coefficient of absolute risk aversion at y_B.

The same procedure can be followed for individual two whose risk premium is:

$$\Pi_2 = \bar{y}_B - F$$

Because Π_2 is greater than Π_1, individual two can be said to be more risk averse than individual one. But, it must be remembered that both the risk premium and the coefficient of absolute risk aversion are only local measures. Therefore, global inferences about risk attitude are not justifiable when this method is used.

The reliability of risk aversion measures derived from mean-variance trade-offs has been questioned because the EV set may not be an unbiased estimator of the means and variances of probability distributions of action choices faced by decision makers. Use of this technique requires either that the probabilities associated with each action choice are normally distributed or that the decision maker has a quadratic utility function. While it is not difficult to obtain unbiased estimates of means and variances required to obtain an unbiased estimate of expected utility, the lack of bias only pertains to the initial probability distribution function. But, substituting the initial unbiased estimators into either the functional form required for a normal distribution or a quadratic utility function will result in biased estimators (Pope and Ziemer).

Other Methods of Measuring Attitudes Towards Risk

All of the methods of determining attitudes towards risk discussed so far rely on the discovery of an individual's utility function over wealth or income or the development of an isoexpected utility function. In contrast to these methods is that used by the observed economic behavior approach which assumes that the degree of risk aversion manifested by individual farmer's can be derived from the difference between their actual behavior and that which is considered to be economically optimal under the assumption of linear utility. It is assumed that if the initial model accurately describes the farmers decision environment, then the difference between optimal input levels and those actually used by the farmer are caused by the farmer's aversion to risk. The validity of the results obtained is conditional on how well the specified model describes the decision environment. This model will be discussed in greater detail within the context of its empirical application by Moscardi and de Janvry in Chapter 5.

While the observed economic behavior approach uses mathematical programming to derive numerical measures of farmers' attitudes towards risk, many programming models only seek to discover whether risk aversion of some type is needed as a constraint to accurately predict farmers' choices. Examples of this approach can be found in Chapter 6.

Summary

Perhaps the most important conclusion to be drawn from this discussion of measures of attitudes towards risk is the caveat that these measures are in fact local measures and cannot justifiably be used to order individuals according to their attitudes towards risk "in the large." Despite this warning, most empirical applications of the expected utility hypothesis and other models of decision making under uncertainty which derive local measures of attitudes towards risk employ them in generalized conclusions about risk attitudes of a population or the ordering of individuals within the population. Examples of this can be seen throughout the studies discussed in Chapters 5 and 7.

IV. DERIVING UTILITY FUNCTIONS

Most efforts to measure risk attitudes within an expected utility framework require that a utility function be determined for each member of the sample. Several simplifying assumptions are commonly employed in this process. In this chapter, methods for eliciting utility functions, determination of their functional form, and the validity of common simplifying assumptions will be examined.

Methods for Directly Eliciting Utility Functions

In the directly elicited utility approach (DEU), a respondent's utility function is derived from his response to a series of hypothetical gambles. Although the structure of the gamble varies with the method used, the basic concept remains the same. The measurement of an individual's preferences requires the assumption that he can identify the most and least favorable outcomes of any action choice. These extreme outcomes are then used to construct a series of gambles over the relevant range. By adjusting either the value of the outcome or its probability of occurrence, a point of indifference between two gambles can be obtained. After a sufficient number of indifference points are obtained, a utility function can be derived using either statistical or graphical methods. Three game structures have been devised for directly eliciting utility functions: the standard reference contract or von Neumann-Morgenstern model; the equally likely risky prospects with a certainty equivalent, or modified von Neumann-Morgenstern model; and the equally likely but risky outcomes or Ramsey model.

Using the standard reference contract method, the analyst finds the best and worst possible outcomes facing the decision maker and assigns arbitrary utility values to them. Probability values which sum to one are chosen and assigned to the outcomes of the gamble and the respondent is asked how much he would pay to play the resulting lottery. Once this indifference level of income is found, its utility measure is obtained by setting it equal to the expected utility of the gamble. Utility values for other levels of wealth are found by varying the probabilities in the lottery.

Three specific criticisms have been directed at this model. First, if the individual has a utility or disutility for gambling his response will be biased by the fact that he is given a choice between the outcome of a gamble and a certain event. Secondly, this technique assumes that the individual's perception of the probabilities of occurrence of the two events in the gamble (his subjective probabilities) are identical to the assigned probabilities or that the individual is willing to accept the assumptions of the game while he is playing it. Third, biases may result from preferences for specific probabilities. Menger has argued that probabilities near one-half tend to be overvalued vis-a-vis probabilities near zero or one. Samuelson has stated that small probabilities tend to be overvalued.

The equally likely risky prospects with a certainty equivalent (ELCE) method was designed to overcome biases due to preferences for specific probabilities by assigning "ethically neutral" or equally likely probabilities to outcomes. Although this method overcomes biases due to probability preferences, it is still subject to the biases which may arise from attitudes towards gambling or from divergence between subjective and objective probabilities. Scandizzo and Dillon have criticized the use of equal probabilities in presenting gambles to peasants since "in a simple two-alternative bet, variance is completely confused with range, and skewness is completely confounded with the relative values of the probabilities, it is clear that a risky prospect has to have both unequal outcomes and unequal probabilities to display the minimum characteristics of randomness required to produce a subject's reaction." Therefore, they argue, "...(I)t is important that the risky prospects presented clearly contain not only a general element of uncertainty (i.e., there is no guarantee that even the expected value of the prospect is achieved over a small interval of time), but also 'distributional' risks (i.e., the possibility that particularly unlucky sequences of bad years materialize)."

The equally likely but risky outcomes (ELRO) method also uses neutral probabilities but reduces biases due to utility or disutility for gambling by presenting the subject with a choice of two gambles instead of a gamble and a sure outcome. In this model, the individual is presented with a .5 chance of winning "a" and a .5 chance of winning "c." He is then presented with an alternative gamble with only one of the two outcomes, a .5 probability of winning "b" specified. The respondent then selects a level of outcome "d" which would be required before he were indifferent between the two gambles. At the chosen level for "d", $U(A) + U(C) = U(B) + U(D)$ and the utility interval "a" to "b" equals the utility interval "c" to "d" because $U(A) - U(B) = U(C) - U(D)$. Additional games are then played which result in points of equally spaced utility until a complete utility function is developed over the relevant range of outcomes.

The ELRO or Ramsey method is quite similar to the method used to measure the utility for income in a riskless situation. The pure utility for income can be measured by ascertaining a level of income, y, at which the satisfaction gained from increasing from y_1 to y would equal the satisfaction of increasing one's income from y to y_2 where $y_1 \leq y \leq y_2$. In other words, we can measure the simple utility for income by finding y such that:

$$U(y) - U(y_1) = U(y_2) - U(y)$$

Arbitrarily assigning utility values to $U(y_1)$ and $U(y_2)$ allows us to solve for U(y). Repeating the procedure allows the assignment of utility values to other income values (Sarin). Note that this method for determining utility of income, in contrast to the ELRO or Ramsey method, involves no concommitant assignment of probabilities. Utility functions derived in this manner, therefore, involve no chance taking.

Officer and Halter tested the predictions made from utility functions elicited using the standard reference contract, ELCE and ELRO methods against the actual fodder reserve plans used by five farmers in New South Wales, Australia. The mean and variance of the actual fodder reserve program used by each farmer were determined as were the mean and variance of twelve alternative reserve programs. The expected utility of each fodder reserve program was estimated using the costs of fodder reserve programs which ranged from zero to twelve months of reserve, and the three utility functions derived for each farmer. The utility functions developed for each farmer were not limited to a specified functional form but were selected on the basis of the highest R^2 value.[1/] All of the functions were non-linear and indicated risk aversion. The fodder reserve program with the maximum expected utility was designated as the predicted decision for that utility function. The farmers' actual fodder reserve programs were compared to the fodder reserve choice predicted by the criterion of minimizing expected cost and by each of the three utility functions. Error was measured as the difference between the predicted and actual months of fodder reserve held.

[1/] R^2 is not a good criterion to use when selecting the proper functional form of the utility function because it does not compensate for varying degrees of freedom found in the linear and higher order equations. A more appropriate criterion is $\bar{R}^2$ which compensates for the differing degrees of freedom.

The average error of prediction using the utility function derived via the standard reference contract method was 1.039 months of fodder reserve, while the average error using the ELRO method was .726 months of fodder reserve. The average error using the ELCE method was only .390 months. The criterion of minimizing expected cost resulted in an average error of .628 months of fodder reserve held.

One year later, the farmers were reinterviewed and their utility functions were elicited using the ELCE and ELRO methods. They were also presented with their original fodder reserve program and that which was selected using the criterion of maximizing expected utility. Some of the respondents chose to alter their preferred fodder reserve programs to conform to the expected utility maximizing choice. It was found that the utility analysis using the ELRO method gave accurate predictions 76% of the time with an average error of .26 months of reserve held, while the ELCE method resulted in an average error of .60. The criterion of minimizing expected costs gave accurate predictions only 58% of the time with an average error of .71.

Although none of the subjects showed any apparent utility or disutility for gambling because a gambling bias may occur, the ELRO model is theoretically superior to the other two. But, because it involves significantly less work, the ELCE method may be more practicable.

Functional Form of The Utility Function

Individual utility functions are not theoretically restricted to one shape nor are they restricted to exhibiting a specific series of shapes such as the Friedman-Savage utility function. Instead, the utility function may be linear throughout or it may exhibit linear, concave and convex segments.

Empirical results have shown that individuals do not, in general, have linear utility functions. Friedman and Savage's hypothesis of an "everyman's utility function" has been challenged by results which show not only a wide variety of functional forms between studies, but different functional forms for individuals within the same sample. For example, Halter and Mason found that approximately one third of their sample of Oregon grass seed farmers had linear functions while the remaining two thirds were equally divided between exhibiting quadratic and cubic functional forms of utility functions. Binswanger found that all but one of 118 individuals in his rural Indian sample had non-linear, risk averse utility functions which exhibited increasing partial risk aversion. While Francisco and Anderson found that utility functions of Australian farmers in their study were "S" shaped in 19 out of 21 cases, indicating risk aversion for relatively large gains and risk preference where large losses were concerned, they also found that participant's utility functions had inflection points at widely varying money levels which were not necessarily related to present wealth position.

Other studies, most notably Dillon and Scandizzo's work in northeast Brazil, have shown the importance of the functional form of the utility function for the results obtained regarding attitudes towards risk. To test the hypothesis that farmers have different attitudes towards risk when subsistence is and is not assured, and that small owners and sharecroppers have different attitudes towards risk, Dillon and Scandizzo directly elicited the utility functions of small farmers in northeast Brazil. Instead of presenting the sixty-four sharecroppers and sixty-six small owners with hypothetical gambles involving money outcomes, the gambles were framed within the standard reference contract model in terms of the likelihood of certain yields in numbers of years out of four. Two types of risky prospects were used, yielding two sets of responses for each group of farmers. One involved only payoffs above household subsistence requirements while the second included the possibility of not producing enough to meet subsistence needs.

Risk attitude coefficients were derived from mean-standard deviation, mean-variance, and exponential utility functions. These were specified, respectively, as:

$$U = E + \sigma V^{1/2}$$

$$U = E + \beta(E^2 + V)$$

$$U = \int_{-\infty}^{\infty}(1-e^{\lambda y})(1-e^{\lambda})^{-1}f(y)dy$$

where y is a risky prospect with probability distribution f(y), mean E and variance V. For all three models, estimation of risk attitude coefficient was based on solution of the relationship that the utility of a risky prospect is equal to the utility of its certainty equivalent.

The authors found that conclusions about a population's risk attitudes are highly contingent upon the type of utility function fit in an unidimensional utility context. With the mean-standard deviation model, small owners were more risk averse than sharecroppers and both groups were more risk averse when subsistence was at stake than when it was not. The mean-variance model does not support hypothesis that owners are more risk averse than sharecroppers, although both groups are still more risk averse with subsistence at stake than when it is assured. The exponential form showed both groups to be risk averse, but with little difference between the groups or the two situations.

For many commonly used utility functions, the properties of absolute and relative risk aversion are implicitly constrained by the choice of a utility function or by use of a methodology which requires the assumption of a specific utility function. Although not restricted on theoretical grounds, none of the common utility functions allow for both increasing and decreasing risk aversion at different levels of wealth.

TABLE 4.1

Risk Aversion Coefficient Properties of Utility Functions*

Utility Function	Property of Absolute Risk Aversion Coefficient	Property of Relative Risk Aversion Coefficient
LINEAR	zero	zero
QUADRATIC	always increasing	always increasing
SEMILOG	always decreasing	constant
LOG LINEAR	always decreasing	constant
EXPONENTIAL	constant	always increasing

*Adapted from Lin, Gabriel and Sonka.

Since the development of the Bernoullian utility function for money, the issue of its proper functional form has been debated but not resolved. Early theorists and practitioners preferred the quadratic form of the utility function,

$$U = a + bW + cW^2 \text{ where } b,\ c > 0$$

because, if properly constrained, this function conforms to the risk averters' requirement of a positively sloping concave function. It is also easy to use since, when combined with linear profit functions, it generates quadratic expected utility functions which are easily maximized with currently available programming routines. The quadratic form is also easily fitted by ordinary least squares to utility questionnaire data (Buccola and French).

Criticism of the quadratic form of the utility function began with Arrow and Pratt's identification of an absolute risk aversion coefficient. If the decision maker is more willing to accept a fixed gamble as his wealth increases, the absolute risk aversion coefficient would decline with increases in wealth. This intuitively appealing description of behavior is not possible using quadratic utility functions in which risk aversion increases rather than decreases with wealth.

The semilog form of the utility function has been proposed as an alternative which is more acceptable according to the hypothesis of declining absolute risk aversion. Unfortunately, it has no tractable solution other than through the use of a Taylor expansion with its associated error term. For empirical research, this is an important disadvantage which often overrides the theoretical advantage of its property of declining absolute risk aversion.

Buccola and French explored the use of an exponential utility function as an alternative to the quadratic or semilog functions and then compared the predictive ability of the exponential model to one using a quadratic function for two California tomato producers. Grower number one's responses to a standard reference contract directly elicited utility procedure approximated an exponential shape. Grower number two's responses more nearly suggested a cubic function. Because of a commitment to increasing relative risk aversion, grower number two's utility function was also fit using an exponential form. Quadratic functions were also fit to the data for both respondents.

In both cases, the quadratic function was more concave than the corresponding best-fit exponential function. As money values increase, the quadratic approaches the exponential form below, crosses it, and then approaches the exponential again at high money values. In both cases, the absolute risk aversion coefficients under the quadratic specification are lower than those under the exponential specification below the point at which the two functions intersect. The growers' coefficients are equal at or near the intersection, and the quadratic equation's coefficient of absolute risk aversion rises above the exponential equation's beyond the point of intersection.

In a research context, much of choice behavior under uncertainty is characterized by the absolute risk aversion coefficient. Given the results of Buccola and French's study, researchers need to be wary not only of the utility functional form employed, but also of the feasible expected profit range of the set of risky prospects considered. Exponential and quadratic forms predicted similar choice behavior for expected profit range near the intersection of the functions, but highly divergent behavior elsewhere.

A Generalized Form of Utility Functions

Recent developments in the area of transformation of variables suggest that the appropriate degree of nonlinearity in a utility function does not require an a priori assumption but can be specified by sample observations. Lin and Chang argue that this can be accomplished through the use of a generalized functional form:

$$(1)\quad \frac{U^{\lambda}-1}{\lambda} = \alpha + B\,\frac{M^{\lambda}-1}{\lambda}$$

with an associated risk aversion coefficient:

$$r(M) = \frac{U''}{U'} = -(\lambda-1)\left(\frac{1}{M} - \frac{1}{U} - \frac{\partial U}{\partial M}\right)$$

where is the transformation parameter, U is utility, and M is monetary income or wealth. The generalized functional form equation fit using ordinary least squares is:

$$(3)\quad U_1{*} = B_o + B_1M_i{*} + B_2M_i{}^{2}{*}$$

where

$$U_i{*} = \frac{U_i^{\lambda}-1}{\lambda}$$

$$M_i{*} = \frac{M^{\lambda}-1}{\lambda}$$

and

$$M_i{}^{2}{*} = \frac{M^{2\lambda}-1}{\lambda}$$

According to Lin and Chang, if λ equals one, equations (1) and (3) are the same as linear and polynominal functions, respectively. When λ approaches zero, equation (1) is equivalent to a log-linear form. They argue that, in general, different degrees of curvature of the utility function can be represented through different values of λ. Therefore, the general functional forms provide greater flexibility in the degree and type of nonlinearity than either linear or polynominal functions. It is also possible to transform only U or M so that the generalized equation is equivalent to a semilog form when λ approaches 0.

Lin and Chang used the generalized form to determine whether the Bernoullian utility maximization hypothesis could have predicted a farmer's production decision better than that reported by Lin, Dean and Moore if a better functional specification had been adopted. Using the data from the previous study, the generalized form was fit using a series of λ's and a maximum likelihood technique was used to select the best value of λ. In this case, a λ of -.70 was determined to be the maximum likelihood estimate of the Bernoullian utility function. The choice predicted using the new specification of the utility function corresponded to the actual farm plan used by the farmer; neither the lexicographic nor the expected profit maximization model was capable of predicting this choice.

Buccola argues that a major flaw in the use of Box-Cox transformations to estimate Bernoullian utility functions is the technique's dependence on an arbitrary origin. While a von Neumann-Morgenstern utility function is unique up to a positive linear transformation, adjusting the utility origin in the Box-Cox transformation changes the risk aversion coefficient, incorrectly implying that the decision maker's risk preferences have changed. If the entire right hand side of the estimating equation is augmented to compensate for the change in utility origin, the Box-Cox representation is destroyed. Buccola argues that the sensitivity of the absolute risk aversion coefficient to changes in the utility origin varies with sample configuration and that the high R^2 obtained by Lin and Chang for their semilog fit was due to the existence of a nearly semilogarithmic sample.

The Effect of Flexibility of Functional Form and Magnitude of Possible Outcomes on Utility Function Estimation

Most applications of the expected utility hypothesis reviewed restrict each individual's utility function so that it exhibits only increasing first derivatives even though this restriction is not required by theory. The use of an inflexible functional form and the range of prospects over which the utility function is taken can have a major impact on the outcomes of the analysis.

It is not unreasonable to imagine that individuals will exhibit utility functions of different shapes for prospects involving gains above current wealth and those involving losses. Many studies only examine situations where either small gains or small losses are possible. Even those studies which allow for situations where both gains and losses are possible only allow a utility function with either increasing or decreasing marginal utility.

Consider an individual who, unknown to the researcher, has a Friedman-Savage form utility function as shown in Figure 4.1. If the individual's utility function is fit with a single inflexible functional form over a small, symmetrical range of gains and losses (-y to y), he will appear to be risk averse over the entire range.

Johnson has argued quite convincingly that the restrictions of an inflexible functional form and narrow range of prospects are responsible for the generally accepted assumption that farmers are risk averse. An accurate mapping of an individual's utility function requires consideration of a range of prospects including gains and losses large enough to alter the individuals socioeconomic status as well as allowances for both increasing and decreasing marginal utility over the range of prospects. Both of these are necessary if any inflection points in an individual's utility function are to be reflected in the functions fitted.

Arguments of the Utility Function

Following Bernoulli, utility has been measured over wealth or income, holding everything else constant. More recently, economists and psychologists have argued that the traditional undimensional utility function does not adequately capture the complexity of human cognition or the variability of attributes within a population. Although this argument is, in many respects, a sound one, attempting to incorporate subjective probabilities, decision weights, and multidimensional utility analysis into an expected utility framework opens a Pandora's box of methodological problems ranging from measurement of individual utility to comparisons of utility between individuals.

One of the first models which explicitly incorporated multiattribute utility functions was lexicographic utility maximization. This model has a distinct advantage in that it allows for a hierarchy of wants which are not restricted to those which can be defined in monetary terms. The attendant disadvantage, however, is that it is nearly impossible to make any interpersonal comparison of utility as no two individuals can be assumed to exhibit the same hierarchical

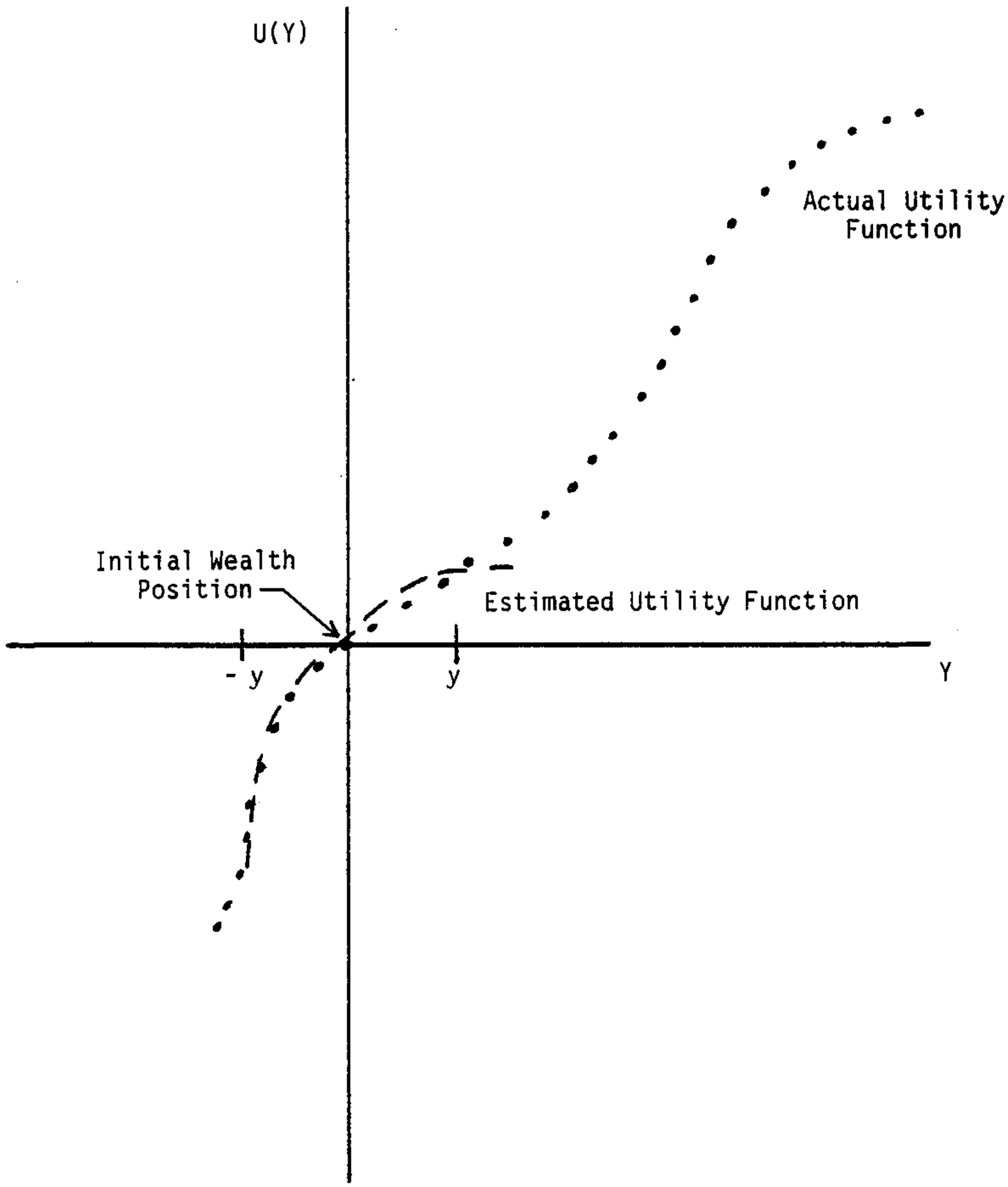

Figure 4.1. An Example of the Effect of Flexibility of Functional Form and Magnitude of Possible Outcomes on Utility Function Estimation.

ordering of preferences. Keeney and Raiffa have developed a method for assessing utility functions for decision makers who face choices with multi-attribute outcomes which are not reducible to homogeneous units. Readers interested in this problem are referred to Keeney and Raiffa's book, Decisions with Multiple Objectives.

There is strong evidence that subjective probabilities are an important factor in determining preference orderings. Davidson, Suppes, and Siegel have shown that individuals' subjective probabilities do not necessarily conform with objective probabilities, even in relatively simple situations such as the flip of a coin. Haneman and Farnworth have shown the effect of differing subjective probability distributions on the pest management decisions made by forty-four cotton growers in California's San Joaquin Valley. They argue that cotton growers' choice of IPM or conventional pest management strategies is based not on differences in risk preferences, but on different subjective probability distributions for the outcomes of each action. It was found that there was no significant difference in the distribution of risk preferences between IPM and non-IPM users. But while each group's subjective probability distribution of yields and profits was correct for their own method, it underestimated the expected value of the other method. Given the subjective probability distributions for partial profits under both control strategies, the current strategy employed was superior to the alternative for 35 of the 44 growers using either an expected profit or an expected utility maximizing decision criterion.

The discrepancy between probabilities may be due, in part, to individuals' ability to revise probabilities "accurately" compared to revised estimates obtained using Bayes Theorem. Francisco and Anderson tested Australian farmers' ability to use fully new information related to the price of wool, lamb markings as a percentage of ewes joined, and annual rainfall in inches. Information use and probability revisions were calculated using the Phillips-Edwards accuracy ratio (AR):

$$AR = \frac{\text{Observed log likelihood ratio}}{\text{Bayesian log likelihood ratio}}$$

where the log likelihood ratio is the difference between the observed log posterior odds and observed log prior odds. The accuracy ratio equals one when subjective revision is identical to the Bayesian revision. In all of the tested cases the accuracy ratio was less than 0.55. This implies that even when participants are given what could be considered to be adequate information regarding the "objective" probabilities, it is unlikely that their subjective probabilities will be identical to the objective ones. Since accuracy ratios vary among individuals, each person in a sample will revise probabilities differently and, therefore will be responding to a different gamble than everyone else even if all are presented with identical "objective" probabilities.

Karmarker has proposed a model of subjectively weighted utility which transforms subjective probability estimates through the use of decision weights. The weighting function employed is not intended to represent perceptions of probabilities. Instead, it is meant to reflect a bias in the way perceived probabilities are incorporated into an evaluation of action choices.

The model is used to calculate subjectively weighted utility (SWU) as:

$$SWU = \sum_{i=1}^{n} W_i U_i / \sum_{i=1}^{n} W_i$$

where U_i is the decision maker's subjective estimate of the utility of the i-th outcome and W_i is a weight reflecting a transformation of the decision maker's subjective estimate of the probability of the i-th outcome occurring. The denominator simply serves to normalize the weights so that they sum to one. W_i's are calculated as:

$$W_i = \frac{(odds_i)^{\alpha}}{1+(odds_i)^{\alpha}}$$

where $odds_i = \frac{\rho_i}{1-\rho_i}$

where ρ_i is the subjective estimate of the probability of the i-th outcome occurring and $0 < \alpha < 1.0$. The bias in the subjectively weighted utility function is a result of α . α can be viewed as a measure of information processing performance or the decision maker's confidence in his subjective probability estimates. At $\alpha = 1.0$ the weighting function sets $W_i = \rho_i$ and no bias exists; as α goes to 0, W_i approaches .5 for all values of ρ_i and all outcomes are treated as if they are equally likely.

Karmarker's model implies that when the range of possible outcome probabilities for all action choices are distributed around a fairly high value (i.e., ρ_i=.8), decision makers should exhibit a preference for less uncertain, low range alternatives, only when the ranges are centered around a relatively low value, decision makers should prefer more uncertain, high range outcome alternatives and, when the ranges are distributed around ρ_i=.5, no preference should be exhibited.

One major problem with the subjectively weighted utility model is that Karmarker does not indicate how α can be assessed independently of its consequences in the model. Furthermore, the hypothesized causal relationship between outcome probability, uncertainty and decision maker preferences was not supported in an empirical test of the theory conducted by Larson. This led Larson to conclude that although α may index a bias in the way perceived outcome probabilities are incorporated into an evaluation of choice alternatives, this bias is not rooted in outcome probability uncertainty.

Kahneman and Tversky also hold that the decision weights that multiply the value of outcomes do not coincide with the attendant probabilities. Instead, they argue that low probabilities are commonly overweighted relative to certainty while intermediate and high probabilities are underweighted. The underweighting of intermediate and high probabilities reduces the attractiveness of possible gains relative to sure ones and reduces the threat of possible losses relative to sure ones. This "certainty effect" leads to violation of the substitution axiom of the expected hypothesis. In prospect theory, an individual's outcome weighting mechanism is represented by a value function. Risk aversion or seeking is explained by the curvature of this function which is usually concave for gains and convex for losses.

The shape of the value function is explained by the "reflection effect" whereby the preferences expressed for negative prospects are the mirror image of those for positive prospects. In other words, the reflection of prospects around zero reverses the preference ordering. As a result, risk aversion in the positive domain is accompanied by risk seeking in the negative domain. In conjunction with the certainty effect this leads to risk seeking preference for a loss that is probable over a smaller loss that is certain. This seems to eliminate aversion to variability, at least with respect to losses, as a plausible explanation of behavior. In addition, the function for losses is much steeper than that for gains. If given an equal probability of losing \$y or gaining some amount, individuals usually demand that the potential gains be a multiple of \$y before they will engage in the gamble.

Kahneman and Tversky reject the assumption of classical analysis that preferences reflect a comprehensive view of the options available to the decision maker. Instead, they argue that people commonly adopt a limited view of the outcomes of decisions: they identify consequences as gains or losses relative to a neutral point. This can lead to inconsistent choices regarding the same objective consequences because the action choices can be evaluated in more than one way, depending upon the reference point with which the outcomes are compared.

In developing prospect theory, Kahneman and Tversky cite several violations of the axioms of the expected utility hypothesis. One of these is framing, the effects arising when the same alternatives are evaluated in relation to different points of reference. Framing effects in consumer behavior may be particularly pronounced in situations which have a single dimension of cost and several dimensions of benefit.

To simplify choices, individuals often disregard components that are shared by all prospects under consideration and focus on their differences. This "isolation effect" may produce inconsistent preferences since a pair of prospects can be decomposed in many ways and the different decompositions may lead to different preference orderings.

Prospect theory distinguishes two phases in the choice process. In an initial editing phase, a preliminary analysis of the offered prospects is carried out, often yielding a simpler representation of the prospects. The second phase is one in which the edited prospect with the highest value is chosen. Editing involves several separate actions including coding, where gains and losses are assessed relative to some neutral reference point, combining, where the range of prospects is reduced by combining the probabilities associated with identical outcomes, segregating, where the risky component of a prospect is separated from the riskless component, simplifying, where extremely unlikely outcomes are discarded and other outcomes are rounded, and dominance, where dominated outcomes are rejected.

Many of the apparent inconsistencies in preference ordering result from editing. In the evaluation stage, a decision weight is associated with each probability affecting the impact of probability on the overall value of the prospect. The resulting value is not a probability measure and the summation of the values is typically less than unity. Using the value function, a weight is assigned to each outcome which reflects the subjective value of that outcome. The resulting set is a measure of the values of deviations from the reference point, or the expected gains or losses associated with each prospect.

Although the evaluation procedure suggested by prospect theory is procedurally similar to that used in expected utility analysis, the two processes are qualitatively different. Prospect theory seeks to explicitly incorporate the subjective impact of probabilities into the utility analysis through the specification of a value function. However, rather than proposing methods to measure the value function, Kahneman and Tversky suggest that it is a standard function across individuals, even though it is not well behaved near probabilities of zero or one. In some respects, this assumption undermines the initial intent of including decision weights as an argument which would account for variations among individuals. Nevertheless, this descriptive model of preference formation also presents challenges to the expected utility hypothesis because it is far from clear whether the effects of decision weights, reference points, and framing should be treated as errors or biases, or whether they should be accepted as valid elements of human experience.

Janis and Mann argue that many decisions are made under high levels of stress which influence the decision makers behavior. They describe five different coping models used by individuals depending on the level of stress to which they are subject. In the unconflicted adherence model the risks associated with maintaining the status quo are small. As a result, there is no consideration given to alternative action choices and no attempt is made to change. In the unconflicted change model the risk associated with not changing is high while the stress associated with the change is low. The action choice selected is the one which is most highly recommended and alternative choices are not explored or considered. The defensive avoidance model is characterized by high levels of stress. The decision maker attempts to shift responsibility, procrastinate, and remain inattentive to new information. Because the decision maker does not believe that a better course of action is available, he fails to examine alternatives. High stress levels also characterize the hypervigilance model in which the decision maker seizes on hastily contrived solutions, overlooking the full set of consequences because of his excitement. In contrast to these four models, the vigilance model is the one followed by an EUH rational man. Under moderate stress levels, the decision maker carefully assimilates and weighs information regarding possible action choices and appraises each choice before making a decision.

Another study proposing still different axioms of rational behavior is Tamerin and Resnik's study of cigarette smokers. In contrast to risk takers who bear risks because of potential monetary awards, the risks taken by smokers or other substance abusers can be described as impulsive. This type of risk taking appears to exhibit the absence of a rational evaluation process and fails to conform with the EUH model. Consequently, a more complicated utility model is needed with psychological arguments to account for pleasure obtained from activities in which the objective risks are exceedingly high.

In order to explain the deviations from "rational" expected utility maximizing behavior which can be explained via an unidimensional utility function over money, several new arguments must be added to the utility function. Only a few additional arguments have been mentioned; there are doubtlessly numerous others. The resultant utility measure would be a function of income or wealth, probabilities, stress levels, pleasure and satisfaction of nonpecuniary wants.

Summary

The single argument utility function provides the fundamental tool of the expected utility hypothesis which, in turn, is the basis for much of the disciplinary work on uncertainty today. But questions about its derivation and the arguments included are causing some economists to reexamine its use.

One of the fundamental assumptions of utility function derivations which has been questioned is that individuals can accurately reduce their utility for wealth in terms of a single, precise number. Second is the question of whether a utility function derived in a contrived choice situation can be used to accurately predict real world situations. Third, and perhaps the most important, is the debate over what arguments need to be included in the utility function. The logic of the argument that factors such as attitude towards gambling, subjective probability or decision weights, stress levels, and bounded rationality should be included as arguments in the utility function must be weighed against the costs of foregoing the use of the EUH as a tool while new methods for their measurement and incorporation into utility functions are being developed. The last major question is what functional form the utility function should exhibit. It has been shown that the functional form assumed has important implications not only for the action choices predicted, but also the attitude towards risk attributed to the decision maker.

The studies reviewed in Chapters 5, 6 and 7 as a whole assume away these questions. In examining the results of these studies, it is important to bear in mind the questions raised in this chapter.

V. EMPIRICAL MEASUREMENT OF FARMERS' ATTITUDES TOWARDS RISK

During the past three decades, numerous field studies have been carried out which measure farmers' attitudes towards risk within the context of expected utility models. Risk attitudes have been determined through the use of a variety of techniques. The interviewing method derives risk attitude coefficients from utility techniques described in the first part of Chapter 3. The experimental approach, which assumes a particular functional form of the utility function for all members of the population, uses choices between sets of gambles with real payoffs to determine the individual's local attitude towards risk. In contrast to these two approaches, the observed economic behavior approach does not require the direct participation of the sample population. The risk attitude coefficient is determined by examining the difference between optimal and observed levels of input use. Yet another approach is to use risk premiums to derive risk attitude coefficients through mathematical programming techniques.

All of these approaches embody assumptions regarding the validity of a hypothesis, initial conditions, and auxiliary assumptions. With only a few exceptions, the studies do not incorporate tests of these assumptions. In this review of the literature on the measurement of attitudes towards risk, particular attention will be paid to the specification of initial conditions (statements describing the state of the system) and the validity of auxiliary assumptions (for example, that the utility function is measured accurately).

The Interviewing Approach

In studies by Halter and Mason and then Whittaker and Winter of the risk attitudes of 44 Oregon grass seed farmers, it was assumed that decision makers select action choices according to an expected utility model. Initial conditions were that the farmers' income reflects the outcome of the preferred farm plan, that the actual farm plan is identical to the preferred farm plan, and the auxiliary assumptions were that the utility function can be measured accurately using the equally likely but risky outcomes model, and that subjective probabilities are identical to objective probabilities.

It was found that equal proportions of the group exhibited linear, quadratic, and cubic functional forms of utility functions. When the Arrow-Pratt measure of absolute risk aversion was evaluated at each farmers' 1973 gross income level, equiproportional groups of farmers were risk averse, risk loving, and risk neutral. Halter and Mason do not specify the coefficients found, but comments by Whittaker and Winter indicate that the average was +.40, implying slight aversion to risk.

Whittaker and Winter attempted to replicate Halter and Mason's study three years later. The authors do not indicate whether individuals were restricted to the same functional form of the utility function as was fit in 1973, nor do they indicate the distribution of functional forms or risk attitude coefficients. They do state that the average absolute risk attitude coefficient, measured at each farmers own 1976 gross income level, was -.29, implying a slight preference for risk.

The shift in the average absolute risk attitude coefficient between 1973 and 1976 raises questions about the validity of the auxiliary assumptions employed. Without more information than that provided by the researchers, discussion of this question becomes speculative in nature. The shift in the average risk coefficient could be the result of interviewer bias, changes in the functional form fit for each farmer's utility function, or might provide strong support for the hypothesis that attitudes towards risk are not invariant over time.

The possibility of interviewer bias resulting in significantly different utility functions was supported by Binswanger in a study in rural India. Binswanger divided his sample in half and had each subsample interviewed in opposite order by two teams of trained interviewers. He found that in each village, the same team of interviewers classified the respondents as more risk averse than did the other set of interviewers, regardless of which team had surveyed that village first. Those differences were statistically significant, often resulting in the reclassification of the respondent from risk preferring or risk neutral to extemely risk averse.

Without knowing whether the utility function fit to the 1976 data was restricted to the same functional form used in 1973, one could also speculate that the change in risk attitude coefficients was a result of the use of a different functional form and not of a shift in preferences. For example, if the same individual had a fitted utility function which was quadratic in one year and cubic in another, even if their income did not change, their evaluated risk attitude coefficient could change dramatically, as shown in Figure 5.1.

Although Halter and Mason and Whittaker and Winter were able to produce a numerical measure of attitudes towards risk, their studies add little to our understanding of decision making under uncertainty. Because the Arrow-Pratt coefficient was taken at each farmer's own gross income level, interpersonal

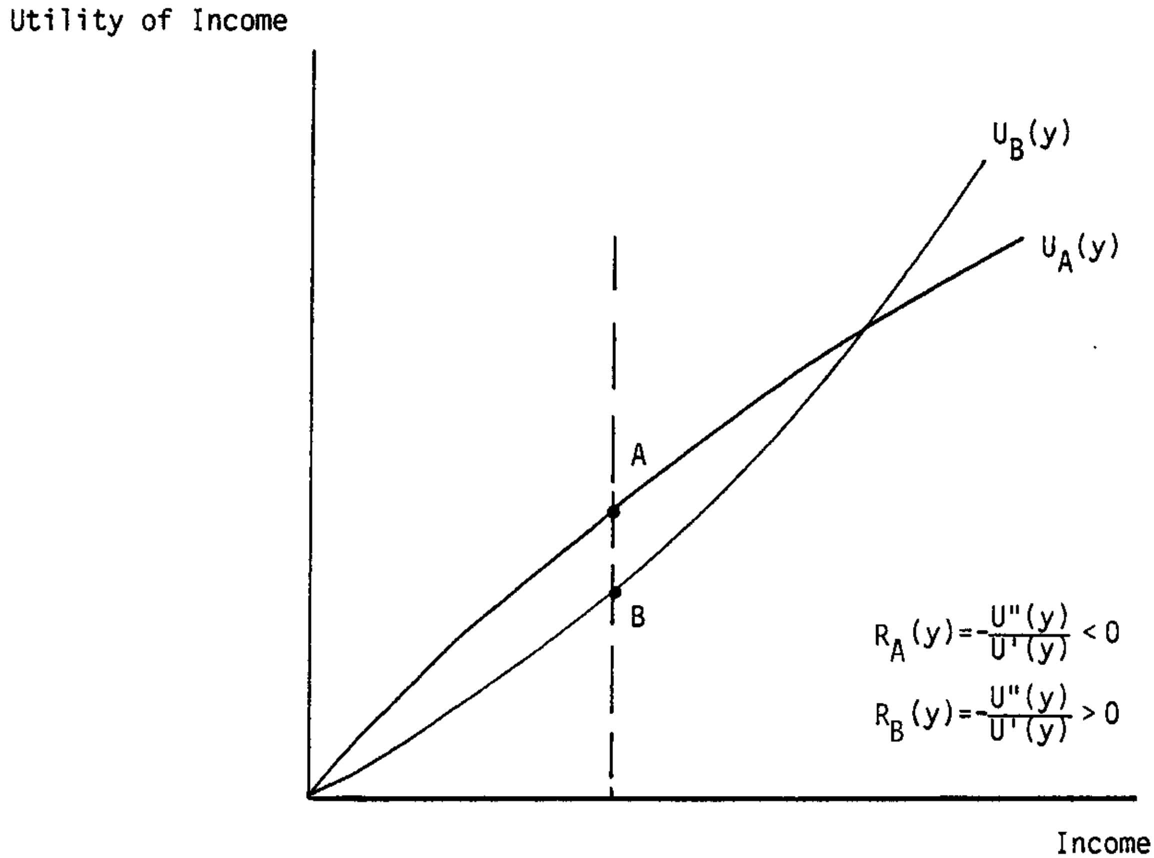

Figure 5.1. Effect of a Change in Functional Form of the Utility Function on the Coefficient of Absolute Risk Aversion

comparisons of risk attitude are only comparisons of present attitude towards risk. Except for farmers with linear utility functions, the coefficients do not even provide a general ranking of risk attitudes. If two farmers shared an identical utility function such as the one shown in Figure 5.2, but had different incomes in 1973, one might incorrectly conclude that Farmer A was more risk averse than Farmer B, even though the farmers would have the same absolute risk aversion coefficient for any given level of income.

In a study of risk attitudes of farmers in northeast Brazil (discussed in Chapter 4), Dillon and Scandizzo employed many of the same initial conditions and auxiliary assumptions used by Halter and Mason and Whittaker and Winter. In the course of their research, Dillon and Scandizzo tested some assumptions while leaving others unvalidated. To ensure that attitudes towards gambling and subjective probabilities for yields would not bias results within the sample, it was ascertained that both sharecroppers and small owners in the sample were able to denominate yield probabilities in terms of chances out of ten and that they had quite similar attitudes towards gambling and subjective probability distributions for yields. Two assumptions that were not tested, but which may be critical in a developing country context, are that farmers' choices can be modeled via unidimensional utility functions with an argument in monetary units and that there is perfect substitution between cash and the market value of subsistence.

When risk attitude coefficients were derived from mean-standard deviation, mean-variance, and exponential utility functions, it was found that conclusions regarding risk attitudes are highly dependent upon the functional form of the utility function. Dillon and Scandizzo also found that in an expected utility context the distribution of peasant risk aversion coefficients is very wide and not necessarily well represented by an average population value.

The Experimental Approach

Results of studies employing interviewing methods have been questioned because of the hypothetical nature of the games which respondents are asked to play. Although Dillon and Scandizzo's method of using gambles framed in terms of actual farm yields reduced the level of abstraction faced by the respondent, they were still hypothetical gambles. It has been argued that the responses given to such gambles may not be the same as would be given if the outcomes were real. In order to reduce the distortions which may arise from the use of directly elicited utility methods, Binswanger determined the risk attitudes of 330 Indian villagers using gambles with real payoffs.

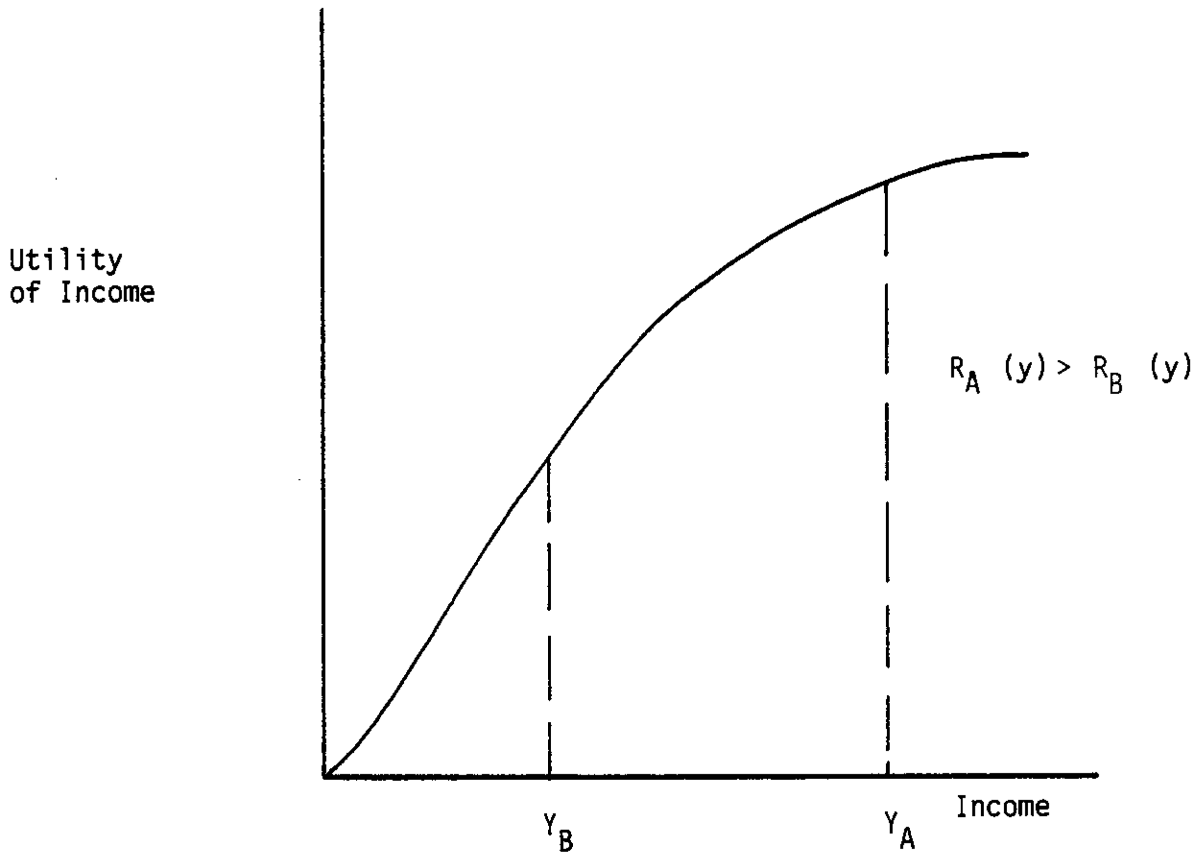

Figure 5.2. Effect of Different Income Levels in Risk Attitude Coefficients of Two Individuals Who Share the Same Utility Function

Binswanger's first step was not to derive a utility function using DEU techniques. Instead, he assumed a constant partial risk aversion utility function of the form:

$U = M(1-S)1-S$

where M is the certainty equivalent of a new prospect and S is the partial risk aversion coefficient which is, theoretically, fixed for each individual regardless of the level of payoff.

Individuals were asked to select a preferred gamble from a set of eight. The games were structured in a mean-variance framework with higher expected returns obtainable at the cost of higher variances. The worst possible outcome of any game was a zero gain and subjects were not faced with any budget constraints. Farmers' partial risk aversion coefficients were derived from their preference ranking of alternative gambles. To simulate actual decision making processes, individuals were given several days to discuss the choice of gambles with relatives and friends before being required to state their preferences.

Among the assumptions made at the outset of the study were that decision makers select action choices according to the expected utility model, that all individuals exhibit constant partial risk aversion, and that preference rankings of alternative real gambles accurately reflect farmers' actual preferences.

Several reliability tests were conducted with the participants. It was found that at prize levels of half a rupee and five rupees, gift money did not differ from behavior with the individual's own money. It was also determined that after individuals became familiar with the game, they could predict in a hypothetical situation how they would respond to an actual gamble. Although this proved to be the case when moving from the five rupee to the fifty rupee game level, amounts of money which are within the typical level of transaction carried out by villagers, one should be extremely cautious in assuming that this will hold in a move from the fifty to the five hundred rupee game as the latter represents a real windfall gain for the average villager. Binswanger was also able to show that there was no automatic tendency to select alternatives in the center of the distribution of gambles.

The result of actual gambles played at the half rupee, five rupee, and fifty rupee levels, and a hypothetical game played at the five hundred rupee level, showed that at low game levels the distribution of partial risk aversion coefficients was fairly evenly spread from risk neutrality to intermediate risk aversion. As the game levels rose, the distribution shifted to the right and became more peaked, showing higher degrees of risk aversion. For individuals with initially low risk aversion, their risk aversion coefficient tended to rise rapidly for games beyond trivial levels. For individuals who initially had moderate levels of risk aversion, the level increased slowly or remained constant as the game level rose. The results violate the theoretical assumption that partial risk aversion will remain constant regardless of the level of payoff involved (Zeckhauser and Keeler).

Interpreted in an expected utility framework, the evidence suggests that all but one of the individuals had nonlinear risk averse utility functions which exhibit increasing partial risk aversion. This conflicts with one of the study's initial assumptions--that all individuals have a constant partial risk aversion utility function--and raises doubts regarding the validity of the methods used.

In essence, Binswanger has assumed initially what he later tries to measure. If this approach is valid, then the assumed utility function described by the empirically obtained parameter can be used to predict the actual choices made by the decision maker. None of the studies which use this method have verified the results by testing the assumed utility functions' ability to predict the preferred action choice from a choice set other than the one used to develop the utility function.

Grisley and Kellogg used the methods proposed by Binswanger to derive the partial risk aversion coefficients of forty farmers from two widely separated villages in the Chaing Mai Valley of Thailand and test the hypothesis of increasing partial risk aversion. The subjects were offered opportunities to participate in five games that each included eleven alternatives. Each game was a multiple of three of the preceding games, implying that there was both an increase in risk and an increase in wealth for each individual alternative across the five games. If individuals were increasingly partially risk averse they would initially prefer more risky alternatives, but select less risky alternatives as risk increased in successive games.

The hypothesis of continuously increasing partial risk aversion was not supported by the results. Increasing partial risk aversion was evident over games two, three, and four, but decreasing partial risk aversion occurred in the ranges of games one to two and from game four to five. It can be speculated that the lower levels of partial risk aversion found in these two ranges is a function of the level of payoffs involved. In the first case, the monetary payoff was of a trivial nature. In game five the lowest payoff was of greater magnitude than the average amount of cash held in many households. Thus, even the minimum amount that could be won represented a significant gain and may have induced farmers to bear greater risks.

Although the experimental method does have the advantage of being able to observe real choices and gives the farmer time to reflect, it shares many of the problems of hypothetical questioning techniques. Davidson, Suppes, and Siegel found in laboratory experiments that using a flip of a coin to determine the outcome of the gamble (the technique used by both of the experimental studies) did not eliminate the problem of subjective probability biases as not all participants had subjective probabilities of one-half for each side of the coin. In addition, utility or disutility for gambling may bias results because participants are given the option of receiving a fixed amount instead of participating in a gamble. Thus, they have a choice between a gamble and a sure outcome. If learning does occur as the series of gambles progresses, as has been suggested by Binswanger, the choice to not participate in some gambles will leave some subjects with lower levels of learning.

In deriving partial risk aversion coefficients it is assumed that the participant maintains the same wealth level throughout the series of gambles. If he plays each gamble, however, his wealth position will change substantially within a brief period of time. Mosteller and Nogee have reported that the amount of money which an individual has before him, such as the winnings from a previous gamble, will affect his decisions. In both studies it is impossible to lose over the series of games and the average return is greater than most participants' monthly income. Knowles believes that this and other factors lead the participant to treat the money as "funny money" and not as real wages.

The Observed Economic Behavior Approach

Both the directly elicited utility and experimental approaches require active farmer participation in some type of game or gamble. In the observed economic behavior approach, it is assumed that the degree of risk aversion manifested by individual farmers can be derived from the gap between their actual behavior and that which is considered to be economically optimal. The validity of the results is conditional on how well the specified model describes peasant behavior. To determine that the observed economic behavior is consistent with initial conditions, auxiliary assumptions and the model of decision making used requires information about the action choices facing the decision maker, probabilities associated with each action choice, and the decision maker's perference function. For complex decisions, acquiring this information is both difficult and costly.

In determining the attitudes towards risk of forty-five farmers in Puebla, Mexico, Moscardi and de Janvry argue that given a production technology, the risk associated with production, and market conditions, the observed level of factor use reveals the underlying degree of risk aversion. The authors begin with the safety-first rule proposed by Kataoka which is:

Maximize y subject to $P(y_i \leq y_d) \leq \alpha$

where y_i is the level of returns, y_d is the disaster level, and α is the acceptable probability of disaster. Moscardi and de Janvry assume that the accepted probability of a disaster is dependent upon a vector of variables, S, which represent the households' socioeconomic characteristics such that $\alpha = \alpha(S)$. By assuming that the mean, μ, and the standard deviation, σ, of y_i are known, a certainty equivalent of the safety-first model can be obtained.

Following Pyle and Turnovsky, y_i can be transformed into the standardized variable:

$$\left(\frac{y_i-\mu}{\sigma}\right)$$

which has a distribution function F. Since F is monotonic, the constraint $P(y_i \leq y_d) \leq \alpha$ can be written in the form $y_d \leq \mu + F^{-1}(\alpha)\sigma$ where $F^{-1}(\alpha)$ is the inverse of F and is a constant, depending on the probability level, α. Kataoka's safety-first criteria can be restated as:

Maximize $\mu + F^{-1}(\alpha)\sigma$

If $((y_i - \mu)/\sigma) = k$ is a constant representing the marginal rate of substitution between expected net income and risk, and $V(\mu,\sigma)$ is the expected utility of income, the model can be written as:

Maximize $V(\mu,\sigma) = \mu - K\sigma$ for $K = K(S)$

Assuming that this model correctly specifies the peasants' decision-making process, the value of the risk aversion parameter, K(S), can be deduced from the observed levels of products and inputs by solving:

$$K(S) = \frac{1}{\theta}\left(\frac{\rho_i X_i}{\rho f_i \mu_y}\right)$$

where P_i is the price of the i-th input, X_i is the quantity of the i-th input, F_i is the elasticity of production of the i-th input, μ_y is the mean output, and Θ is a risk coefficient.

Because the risk aversion coefficient is treated as a residual and tends to include other sources of disparity between optimum and actual resource allocation in addition to the effect of attitudes towards risk, careful screening of data must be done to ensure that the measure K does not include the effects of constraints such as imperfect markets or capital availability.

The optimum level of fertilizer was the input used and was determined using results from twenty-five test plots supervised by CIMMYT. Nitrogen was selected as the relevant variable because it is agronomically the most important input for increasing yields in the area and is also the largest component of variable costs. The results of this procedure show a distribution of risk aversion which is highly skewed towards the risk averters and centered around K=1.12. A risk neutral farmer would have a K value of zero. To facilitate the use of discriminant analysis in a later portion of the study, K was truncated at 2. Approximately thirty percent of the respondents had a K value between 1.75 and 2.00.

Although the observed economic behavior approach is appealing because it does not require participation in a gaming scheme, the results are subject to error stemming from three sources: specification of a realistic economic optimum level of input use, development of a model which accurately portrays the farmer's decision making processes, and screening of observed behavior to eliminate all sources of discrepancy, except risk attitude, between actual and observed behavior. One possible source of discrepancy in this study is the method by which optimal fertilizer use was determined; it is not uncommon to find that even under "optimal" conditions the level of inputs actually used and yields produced on farmers' fields deviate significantly from those in research trials. Thus, the economic optimum specified using the experiment station production function may be unrealistic. It is also unlikely that the farmer's decision making process is adequately described by a model which includes only the expected value of the marginal productivity of the input and the price of the input compounded by a risk factor. This incomplete model increases the necessity of screening observations to remove all factors other than risk which contribute to the discrepancy between actual and optimal factor use. Evidence that this has not been accomplished is seen when socioeconomic factors are regressed against risk attitude coefficients. It was found that the lower the farmer's off-farm income and the less land under his control, the more risk averse the farmer. Binswanger and Sillers, in an unpublished paper on credit constraints facing farmers, show that both of these factors are major constraints in receiving loans for inputs.

Thus, a credit constraint, not attitude towards risk, may be the cause of lower levels of fertilizer application by low income small farmers.

It is also assumed that the actual farm plan employed is the farmer's preferred choice of plans. Officer and Halter and Lin, Dean and Moore have shown that actual farm plans may not reflect true preferences because of factors constraining the opportunity set of farmers such that they do not contain the utility maximizing choice. In fact, for none of their respondents was their actual farm plan a member of their efficient set. These results should lead us to reconsider the results of observed economic behavior studies as well as safety first studies which assume that the farmer's actual behavior reflects his preferred action choice. This problem can also arise in the reverse, as in the programming study by Brink and McCarl where the farmers' actual cropping patterns were not present in their choice set.

The Interval Approach

Because of the limitations of local measures of attitudes towards risk and the difficulty of directly measuring the utility of income or wealth, King and Robison have developed a method of inferring a global risk aversion function from a measure of average risk aversion. This development is predicated upon the recognition that, over small ranges, an average risk aversion measure is a good measure of the actual Arrow-Pratt function of absolute risk aversion.

The model developed by King and Robison measures:

$$E(U(\Pi,\varepsilon))$$

where Π is the income or wealth and ε is an error term resulting from the failure to measure or hold constant variables other than income or wealth which affect the utility function. Then, using an efficiency criteria developed by Meyer which is consistent with the expected utility hypothesis, the authors carefully selected pairs of distributions to determine risk preferences over intervals within the range of outcomes.

This is a unique approach to risk attitude measurement and is only accurate in terms of quantifiable probability measures. The authors propose an interval measurement which allows for a trade-off between Type I and Type II errors. Type I error is the rejection of the preferred choice from the choice set, while Type II error is the failure to order correctly pair-wise comparisons of action choices. Since the expected utility hypothesis employs a single argument utility function which discriminates on the basis of absolute differences in expected values of outcomes, this approach has a great likelihood of committing a Type I error and very little likelihood of Type II error.

The interval measured by King and Robison can be of any shape or width. The larger the width the greater the likelihood of Type II error (failure to order pair-wise comparisons), and the smaller the Type I error (rejection of the preferred action choice). Methods for determining the optimal interval width to minimize error still need to be developed.

To test this model a series of three questionnaires was administered to graduate students in agricultural economics at Michigan State University. The first questionnaire measured risk intervals of different widths at different income levels. The second questionnaire employed the equally likely with risky outcomes method to derive utility functions. The third questionnaire presented decision makers with a series of choices betweeen pairs of distributions.

In this study, the model predicted correct choices 65% of the time, yielding a 35% Type I error. It also ordered choices correctly 100% of the time for a zero Type II error. The largest interval width predicted correct choices 98% of the time while the smallest interval used predicted choices correctly 75% of the time. The largest interval ordered choices correctly 9% of the time (91% Type II error) and the smallest ordered them 91% of the time (9% Type II error).

Given the difficulties involved in measuring utility functions directly, this may become an accepted method for measuring risk preferences. It remains to be seen how the interval approach will perform when applied in actual choice situations.

The Mathematical Programming Approach[1/]

Bond and Wonder used a combination of directly elicited utility and mathematical programming techniques to derive risk attitude measures for a sample of Australian farmers. Assuming that farmers select action choices according to the expected utility model, Bond and Wonder used the standard reference contract technique to determine the risk premium for income required by 217 farmers who regularly participate in the annual Australian Agricultural and Grazing Industry Survey. The risk premium was used to derive a risk attitude coefficient for each farmer through the use of mathematical programming models whose objective functions directly employed the variance or standard deviation of returns. For example, the certainty equivalent of a range of uncertain income levels can be written into an objective function as:

[1/] Other applications of mathematical programming models are discussed in Chapter 6.

$$X_0 = X^*+1/2V(X)(U''(X^*)/U'(X^*))$$

where X^* is the certainty equivalent, $V(X)$ is the variance of the risky prospect X, and $U'(X)$ and $U''(X)$ are the first and second derivatives of the utility function evaluated at the point X^*. This follows directly from the certainty equivalent formulation developed in Chapter 3.

The standard deviation or the variance can be employed directly yielding objective functions of the forms:

$$X_0 = X^*\emptyset(V(X))^{1/2}$$

$$X_0 = X^*+AV(X)$$

where $\emptyset$ and A are interpreted as risk coefficients. Solving for these coefficients yields:

$$\emptyset = 1/2(V(X))^{1/2}(U''(X^*)/U'(X^*))$$

$$A = 1/2(U''(X^*)/U'(X^*))$$

Bond and Wonder classified farmers as risk averse, risk neutral, or risk preferring depending on whether their risk premium was positive, zero or negative. Farmers who initially displayed risk aversion but switched over to risk preferring responses for later gambles were characterized as being averse to preference. Respondents who vascillated between risk preference and aversion were not classified. This category included almost twenty-five percent of the respondents. The responses to the risk attitude questionnaire are shown in Table 5.1.

TABLE 5.1

Classification of Farmers by Attitude Towards Risk

Risk Attitude	Frequency
Aversion	77
Preference	25
Neutrality	33
Averse to preference	29
Other	53

Estimates of the risk premium and risk attitude coefficients suggested that, on average, there is only a 'moderate' degree of risk aversion in the rural sector but that attitudes towards risk vary markedly between individuals.

Although this method of estimating risk attitudes is appealing in its apparent simplicity, Drynan has shown that it is not possible to meaningfully estimate the risk coefficients, Ø and A, within the context of the expected utility hypothesis. Drynan bases his critique on the assertion that many decision makers have explicit attitudes towards risk such as an inherent dislike for variability measured in terms of variance, standard-deviation, mean absolute deviation, etc. In particular, decision makers who trade-off expected income and variability of income in a linear manner violate the independence axiom of the expected utility hypothesis. Therefore, according to Drynan, Bond and Wonder's assumption that decision makers have a von Neumann-Morgenstern utility function for income is inconsistent with their use of mean-variability models unless it is also assumed that the utility function is quadratic or that the risks assessed belong to a family of risks in which the mean and variance uniquely define the risk. While Drynan's point is useful in drawing attention to the need to carefully state assumptions, it does not substantively distract from Bond and Wonder's results as assumption of the existence of quadratic utility, normal distributions and uniqueness of definitions are implicit in the use of mean-variance models.

Summary

Conventional wisdom holds that farmers are generally risk averse. The evidence presented in this chapter is not in total support of that contention. In fact, farmers appear to share the whole spectrum of attitudes towards risk, from risk loving to risk aversion.

It is difficult to reach more specific conclusions from the evidence presented because the studies and their results are not easily compared. Almost every study which has attempted to measure farmers' attitudes towards risk has used a slightly different method and employed different initial conditions and auxililary assumptions than its cohorts. Given questions regarding the validity of many initial conditions and auxiliary assumptions, it is difficult to determine which of the methods gives the most reliable result. The results obtained are also subject to question in light of Johnson's argument that a utility function can be mapped accurately only if two conditions are met: the range of prospects considered must include gains and losses or changes in the level of income both of a magnitude which would alter the individuals' socioeconomic status, and allowance for both increasing and decreasing marginal utility over the range of prospects. Examination of Table 5.2 reveals that none of the studies reviewed met both of these conditions.

The process of verification is further complicated by the fact that the numerical measures of risk attitude, such as the Arrow-Pratt coefficient of absolute risk aversion and the "K" value determined in observed economic behavior studies, are not reducible to one standard measure. Different studies may also be measuring different types of risk aversion. Berry and Huysam argue that an individual's attitude towards risk is composed of an inherent attitude towards risk which is not a consequence of economic variables or constraints, and induced risk aversion which is income or wealth determined. Observed economic behavior studies of risk attitude measure both inherent and induced risk aversion while the other methods may or may not include both. Chapter 7 examines the proposition that risk attitudes are closely linked with wealth and other socioeconomic variables.

Less obvious, but equally important, are differences which undoubtedly exist in the operational definitions of variables and quality of data used as well as environmental factors which make the results non-comparable. Of particular concern is the importance of measures of income or wealth in obtaining attitudes towards risk (Vincent).

The concept of wealth has limited universal epistemological content. In a society such as the United States where independent action and individual choice are viewed as the norm, it makes sense to inquire as to how an individual behaves under changing states of nature and their own socioeconomic characteristics. In countries where wealth is a group concept and both wealth and the burden of risk are managed through complex social relationships, attempts to compare individuals' attitudes towards risk and correlate them with socioeconomic conditions may be spurious.

The measurement of income raises equally thorny problems. The use of market value of production as a proxy for income has shortcomings in subsistence agriculture where a large proportion of production goes to family consumption. The use of gross margins presents no difficulty in industrialized countries where family labor represents a small portion of the input package and variable input cash costs are a large fraction of total production expenses. However, there are no universally accepted procedures for computing gross margins in the developing world. Rules pertaining to the treatment of home grown inputs and family labor are far from uniform. Therefore, differences in measured risk attitudes and

TABLE 5.2

Magnitude of Gains, Losses, or Changes in Income and Flexibility of Functional Form of the Utility Function Used in Nine Studies

	Were the outcomes of the game framed in terms of one period gains and/or losses or varying levels of income?	Were they of significant magnitude to change the individual's socio-economic status?[1]	Was it possible for the equation fitted to exhibit a combination of increasing and decreasing maginal utility?
Binswanger	one period gains	no	no
Bond and Wonder	gains and losses in income	yes	no
Brink and McCarl	NA	NA	NA
Dillon and Scandizzo	gains and losses in income	yes (losses) no (gains)	no
Grisley and Kellogg	one period gains	no	no
Halter and Mason	gains and losses in income	yes	no
Moscardi and de Janvry	one period gains	no	no
Officer and Halter	one period gains and losses	no	no
Whittaker and Winter	gains and losses in income	yes	no

[1] Examples of gains and losses deemed significant enough to change and indivduals socio-economic status include gains large enough to allow a landless peasant to purchase land or a farmer to buy another farm and losses which would result in bankruptcy or failure to meet subsistence requirements.

their relationship with individuals' socioeconomic characteristics may be explained as much by differences in researchers' and farmers' understanding of the meaning of income, wealth or profit as by the model or methods employed.

VI. MULTIPLE OBJECTIVES AND THE IMPORTANCE OF RISK IN FARM PLANNING MODELS

Linear programming models as conventionally applied to farm planning do not take into account the uncertainty which exists in the production environment. The standard linear programming model assumes profit maximization as an objective function and obtains a single precise prescription of optimal resource allocation which will, theoretically, maximize this objective function. However, we cannot realistically assume that variability in returns due to stochastic processes does not exist or that in the presence of risk the decision maker will maintain a profit maximizing objective.

Numerous researchers have sought to overcome this perceived deficiency in the standard linear programming model by introducing constraints into the objective function. These constraints are assumed to represent arguments other than profit maximization in the farmer's objective function due to the presence of risk or uncertainty. Without an adequate theoretical framework, the selection of constraints in the objective function is arbitrary.

We would, of course, like to be able to test the appropriateness of the assumed objective functions using Giere's two tests of a theoretical hypothesis introduced in Chapter 2. However, in most cases these tests cannot be conducted because the studies either do not compare the farm plan which maximizes the assumed objective function with a farm plan selected by the farmer, or they do not test the prediction made using the assumed objective function against competing models.

Adding Constraints to the Objective Function

Consider the expected profit-variance set OA shown in Figure 6.1. By employing the standard linear programming method of a linear expected profit function and linear constraints, point A, the highest expected profit-variance solution available would be selected.

However, many decision theorists believe that, under risk, farmers are no longer concerned only with profit maximization but have other objectives as well. For example, if the farmer is averse to risk he is willing to sacrifice some profit for a reduction in risk. Therefore, he would select a farm plan such as the one represented by point B in Figure 6.1. It has been proposed that the solution for maximizing this more complex objective function can be obtained by adding more constraints. The form of the additional constraints varies with the objective function assumed.

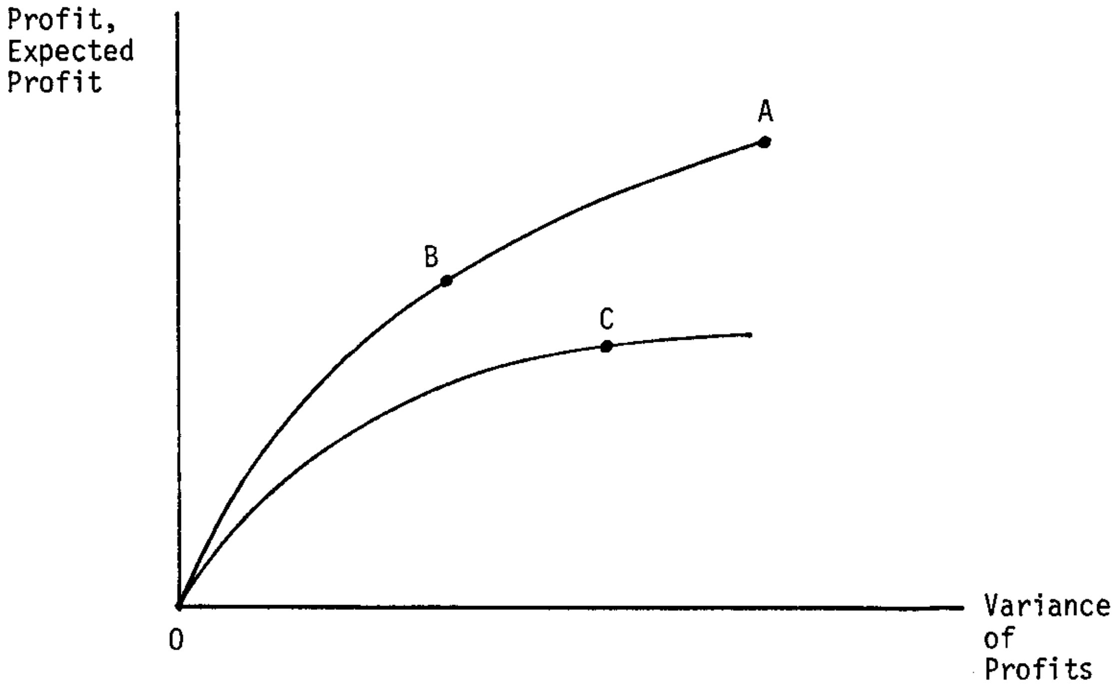

FIGURE 6.1

The Effect of Adding Constraints to the Objective Function to Represent Decision Rules Under Risk

Unfortunately, the additional constraints may not result in the desired solution. Instead, they may well lead to the selection of a point, such as C, an interim solution.

Some "Rule of Thumb" Objectives

Three alternatives to profit maximizing objective functions have been demonstrated by McInerny and Heyer. Solutions have been obtained which are assumed to correspond to actual farm plans which would be selected by farmers who follow maximax, maximin and minimum ex poste regret rules of thumb in decision making under risk. However, the appropriateness of these assumptions have not been tested in any of the studies reviewed.

McInerny (1967) illustrates the derivation of maximum constraints to the objective function within the framework of a one person game against nature in which all of the crop and livestock enterprises are the farmers' resource use alternatives and the states of nature are the different possible prices, weather conditions, etc. which may occur in the planning period.

His model can be viewed as a normal farm L.P. model with additional constraints which ensure that a maximin rather than a maximum level of total gross margin is attained. If n states of nature are considered, these extra constraints will number n-1.

The full model is:

Maximize $V = \Sigma c_i p_i$

subject to n-1 maximin constraints of the form

$$\sum_i a_{ij} p_i = 0$$

and r farm constraints of the form

$$\sum_i d_{ik} p_k \leq b_k \text{ where } p_i \geq 0$$

Where the p_i indicate the proportion of resources that should be allocated to each activity under each state of nature a_{ij}, c_i are gross margins and the value of V will be the maximum minimum gain attainable under the system.

When the model was run using five different assumed states of nature it was found that the maximin objective function did achieve its aim of ensuring a higher minimum level of returns than the profit maximizing function for "worst case" states of nature. Over all five states of nature the average gross margins generated by the two plans were not significantly different.

Although McInerny does show that an assumed maximin objective function will produce solutions consistent with the objective, he gives no indication as to the efficiency of the solutions obtained or any evidence to substantiate his assumption that farmers use a maximin rule of thumb in farm planning under conditions of risk.

McInerny (1969) proposes another objective function for farm planning models: the minimization of ex poste regret. Ex poste regret is defined as the dissatisfaction the farmer feels when he receives a return which is less than the maximum return he could have achieved had he correctly predicted the state of nature in the planning period. The magnitude of dissatisfaction is equal to the monetary difference between the actual and maximum returns.

The minimizing ex poste regret rule of thumb is applied by reformulating the decision matrix to produce a new regrets matrix (r_{ij}) by subtracting, for every state of nature, the actual payoff from the maximum possible payoff. The main difference between the formulation of the objective function for this rule of thumb and the maximin rule of thumb is that outcomes are, in this case, couched in terms of ex poste regrets rather than direct money returns. The optimal farm plan is the one which produces the lowest possible maximum regret (V*). The full model is:

$$\text{Minimize } V^*$$

subject to the minimax constraints:

$$R'P \leq V^*$$

$$IP = L$$

and the farm constraints:

$$AP \geq B$$

$$P \geq 0$$

where R is a matrix of regrets, P is a vector of activity levels, I is a unit vector, L is total acreage, A is a matrix of input-output coefficients, and B is a vector of resource levels. The constraint on land is necessary since, without it, the objective function would achieve its minimum value if no resources were used.

In a comparison of the results achieved with the minimax regret plan with results from maximin and standard L.P. formulations using five states of nature, the minimax regret plan achieved its aim of ensuring that the maximum regret is as low as can be obtained under only one of five states of nature. The minimax regret model also did poorly in satisfying farm income objectives.

Heyer developed farm plans which are optimal using maximax, maximin, and average value maximizing objective functions for best and worst state of nature scenarios for traditional farmers in Kenya with and without cotton enterprises. As would be expected, the solution for the maximax objective function did well under the best state of nature, but fell far below the returns obtained from the average value maximizing plan under the worst state of nature. The maximin solution gave higher returns than the other two solutions in the worst case scenario, but only at the expense of substantial amounts of income in the best case scenario. Maximizing expected returns on average gave results very close to those for the maximax strategy.

Like McInerny, Heyer does not test for the efficiency of the optimal solutions for each objective function, nor does she compare the solutions with actual farm plans to determine if farmers use any one of the three decision rules in farm planning under risk.

The mixed strategy or Hurwicz criterion described in Chapter 2 may also be incorporated into an L.P. model provided that a measure of the individuals pessimistic (α) and optimisitic ($1-\alpha$) attitudes are known. This decision rule states that the optimal farm plan would be the one which maximizes an α* index where:

$$\alpha_i^* = m_i + (1-\alpha)M_i$$

where m_i is the minimum return expected and M_i is the maximum return expected from a particular farm plan under all possible states of nature.

If the coefficients in the objective function are the a_i^* indices for each activity, the resulting solution maximizes an overall α* index. The full model is:

$$\text{Maximize } a^{*\prime}P$$

subject to:

$$AP \leq B$$

$$P \geq 0$$

Where a* is a vector containing the α_i^* index for each activity, P is a vector of activity levels, A is a matrix of input-output coefficients, and B is a vector of resource levels.

While the Hurwicz criterion can be used in an L.P. model without any conceptual difficulty, its practicability is doubtful because of the difficulty of obtaining the α value for any individuals. According to McInerny, Luce and Raiffa have proposed a method for determining an α level through the solution of a simple decision situation. However, this method implies that α is a constant characteristic of the decision maker regardless of the decision situation. This assumption may not be justifiable.

Testing for the Importance of Risk

One of the first attempts to use a mathematical programming model to demonstrate the impact of risk attitudes on farmers' decisions within a safety-first framework was a study of farmers in southern France by Boussard and Petit. Following the assumption that farmers maximize profits, provided that the possibility of ruin is so small as to be negligible, the researchers introduced a focus loss constraint into the linear programming format. This assumption implies a lexicographic order of preferences (Encarnacion). A chance constrained program with a zero ordered decision rule was not used because such a model would require knowledge of the joint probability distribution of receipts by hectare of each crop planted and to be able to combine them to obtain the probability distribution of income obtained from the optimal combination of crops. This would be prohibitively difficult as there are strong indications that neither yields nor prices are normally or symmetrically distributed (Day, Mandelbrot).

In specifying the focus-loss of a cropping pattern, farmers were assumed to diversify so that there is only a small possibility that their incomes will fall to the allowable minimum or below. The authors assume that the focal loss on one crop is only a fraction of the total permitted loss, signified as 1/k. One of the weaknesses of this approach is the arbitrariness of the estimation of the parameters such as the focal loss of each group crop activity, the minimum income, and the fraction 1/k. In this study, the values were determined by extension agents who worked in the region, not by questioning farmers in the sample.

The model employed by Boussard and Petit is:

Maximize Z

subject to the security constraint:

$$AX - BU \leq 0$$

and other technical and credit constraints where Z is the gross margin, A is a matrix of a_{ij}'s, the outcome of activities under different states of nature, X is a matrix of activities and BU is defined by vectors of the total permissable loss and the amount of available capital, a row for minimum permitted income and a row defined as security. Security is defined as:

$$P_iX_i - 1/k \text{ LOSS } \leq 0 \quad (i = 1, 2, \ldots, n)$$

where the variations of riskiness among crops are expressed as P_i's, LOSS is the total allowable loss, and 1/k is the condition that the focal loss on one crop cannot exceed the fraction 1/k of the total loss.

The actual cropping pattern of forty-four farmers was compared with predictions using models containing only technical constraints, only security constraints, and security and credit constraints linked together. The model which included both security and credit constraints predicted actual cropping patterns much more closely than did the other two models. One implication is that both security and credit constraints affect cropping decisions. But since the parameters were based on nonfarmers' estimates of regional focal-loss points and not on individual farmers' responses, the model tells us little about how individual farmers alter their decisions in the face of uncertainty.

In a developing country application, Low employed a linear programming model with safety-first decision criterion which maximizes the cost of providing against ruin. It was assumed that farmers in his sample in S.E. Ghana attempted to maximize expected income subject to ensuring that their subsistence requirements are met under the most adverse conditions likely. Low called this decision rule the minimum cost of security criterion.

The model was tested in S.E. Ghana where uncertainty was introduced through the output level of forest maize, which depends upon the relationship between time of planting and pattern of seasonal rainfall. The security constraint set employed ensured that the maize yield under specified circumstances is at least equal to the maize subsistence requirement. The value of the objective function, therefore, represented the expected income after subsistence requirements have been met. The model was based on the choice situation facing the model village household; restrictions applied to the initial model represent the situation facing households which were less well endowed. It was found that the model's results were close to observed behavior, suggesting that the assumptions used in the model were valid. It was also found that different production patterns employed by farmers with different levels of income or wealth were based on different levels of resource availability rather than on different objectives.

It can be inferred from Low's results that resource constraints and not different objectives or attitudes are responsible for different cropping patterns among farmers in S.E. Ghana. Roumasset's study of fertilizer application decisions of Filipino farmers supports this hypothesis. Roumasset initially assumed that if farmers are especially averse to low levels of income, their behavior can best be described by a safety-first rule of thumb. A risk neutral solution and a risk sensitivity index representing the profit per hectare needed to avoid selling nonliquid assets were formulated for each farmer. The actual amount of nitrogen farmers used per hectare was regressed on the predicted values obtained from a risk neutral and two safety-first models. One model employed the safety-first criterion set forth by Roy:

Minimize $P(y_i \leq y_d)$

where P is probability, y_i is the level of returns, and y_d is some disaster level. The second safety-first criterion used was one proposed by Kataoka whereby the decision maker is assumed to:

Maximize y subject to $P(y_i \leq y_d) \leq \alpha$

where y_i is the level of returns, y_d is the disaster level, α is the probability of disaster, and U is utility. No significant difference was found in the R^2 values for the three models.

Roumasset argues that his results show that supplementing a risk neutral model with additional concern for security does not increase the model's power. However, the results from this study may be influenced by the fact that farmers in this sample were not particularly averse to risk, or because risk was inversely proportional to expected profits for the technique under consideration. Two other factors should be considered. One is that fertilizer cost amounted to only ten to twenty percent of total costs for farmers in the region. Secondly, although the R^2 values may not be significantly different, they were all uniformly low, at about .5, indicating that none of the models was particularly well specified.

Brink and McCarl, in a study utilizing the Purdue Top Farmer Cropping Model, investigated whether or not risk should be introduced explicitly in operational farm planning models. More specifically, they tested whether including consideration of risk attitudes in the model helps to better predict actual farmer behavior in terms of crop acreages chosen. If explicit consideration of risk attitude is helpful, and if the diversity between farmers in terms of their trade-off between expected return and variance of return is small, a common default value for the trade-off can be used.

The portfolio choice model employed used the negative deviation from the expected return as a measure of risk. This required the assumption that outcomes are normally distributed or that farmers have quadratic utility functions. For this study the actual negative deviation was converted to a standard deviation so that the measure would be compatible with that used in other studies. This conversion requires the assumption that total negative deviation is exactly one-half of the total absolute deviation.[1/] Each farmer's 1975 acreage and income data was used to specify the nonrisk portion of the objective function while the risk portion was specified using gross margin outcomes synthesized from historical data and assumed to be constant for all farmers.

Twenty farm plans with a measure of standard deviation between 0 and 1.95 were presented to the farmers. The risk coefficient for each farmer was taken to be the parameterized coefficient which minimized the difference between the associated plan in the choice set and the farmer's present plan measured in terms of total absolute deviation in acreage of each of four crops.

The null hypothesis of no difference in effects of varying risk aversion coefficients was rejected at the .01 level of significance. Several qualifiers should be added to this result. One is that attributing all of the differences to risk embodies strong assumptions since the present farm plan is affected by other factors as well. In addition, the choice set did not include any of the farmers' present mixes of corn and soybeans, suggesting model misspecification. There was no significant difference in results for risk aversion coefficients less than .62. Considerable variation in acreages was observed as the coefficient became larger than this. The majority of the farmers in this sample, who paid to participate in the Top Farmer Cropping Program, had risk aversion coefficients which were less than .25, indicating that risk attitude, in general, is not an important factor in the choice of crop acreages by the study group.

The low levels of risk aversion found by Brink and McCarl may be a peculiarity of their select sample of corn belt farmers. Their results add to the store of conflicting conclusions reached by studies which examine the relative importance of subjective factors such as risk aversion and liquidity requirements and objective factors such as credit or input availability on farmer decision making.

[1/] Hazell (1971) proposes the use of E-A efficient set rather than an E-V efficient set where A is mean absolute income variance. The objective function is the minimization of total absolute deviations (MOTAD). Both estimators are unbiased, but MOTAD is only about 88% as efficient as quadratic programming in estimating the population standard deviation. He points out several advantages of MOTAD including: it may lead to smaller problems (constraints and real activities) for complex farm organizations, duals hold over specified intervals, and contributions of negative total gross margin deviations need not be equal to the contribution of positive total gross margin deviations.

Wiens, in a quadratic programming study, utilized historical Chinese sample survey data to demonstrate that the behavior of peasants facing choices comparable to those confronted elsewhere in Asia today exhibit substantial aversion to risk. Instead of using a quadratic utility function, Wiens assumed an exponential utility of income function, which allowed for the use of information derived from both primal and dual solutions. According to Wiens, the use of dual solutions allows for the discovery of shadow prices and direct estimation of the risk aversion parameter, Ø.

Paris points out that Wien's exclusive reliance on dual constraints to estimate risk aversion coefficients is incomplete. He argues that risk aversion coefficients should either be estimated initially using the primals, or that a primal estimate should be used to check the consistency of the estimates obtained using the duals. Furthermore, "If the estimates of Ø obtained from them (the primal and the dual) are consistent (that is, are almost the same), it should be concluded that entrepreneur's actual choices of output levels are optimal and no need exists to perform further optimizations. In other words, the utilization of the estimated Ø in the quadratic programming model (in conjunction with the same data used to compute Ø) merely corresponds to a tautological exercise" (Paris, p. 273).

The primary decision problem examined by Wiens was the determination of the amounts of owned and hired factor services to devote to cotton, maize, and sorghum, each of which have markedly different degrees of yield stability and initial cash outlay requirements. The crops shared a single growing season and, because of a properly functioning market in pre-revolutionary China were viewed as substitutes. When estimates of the risk aversion parameter were made for large and small farm operators it was found that decreasing absolute risk aversion with increased wealth was required to explain the behavior of both groups. To ascertain that the same results would not be obtained with a risk neutral model or when working capital was treated as the sole constraint, additional runs were made. The results of the risk neutral model were inconsistent. When working capital was constrained in the risk neutral model, specialization in cotton or maize was optimal. In contrast, the risk aversion model conformed with the average behavior of the peasants with primal solutions calling for full diversification among the three crops in proportions similar to those actually observed. This model also reduced the differences between dual solutions and market prices.

Summary

Unfortunately, the literature does not give us any clear direction on either the importance of including risk considerations in mathematical programming models used for farm planning or what form these considerations should take in the objective function.

One of the fundamental assertions underlying safety-first and rule of thumb models reviewed above is that decision problems cannot be collapsed into a comparison of the expected value or utility of the outcomes of action choices. Supporters of these hypotheses assert that other factors, such as the disaster level of outcomes, must become a focal point of decision analysis. Incorporation of these objectives into farm planning models applied to real world situations has led to conflicting results.

Low and Boussard and Petit found that resource availability and security and credit constraints influenced farmers' cropping decisions more than did different objectives held by farmers. Studies which attempted to determine the effect of attitudes towards risk on cropping decisions within a safety-first and focus loss constraint also found conflicting evidence. While Roumasset argues that farmers are risk neutral and that consideration of risk attitudes does not ehnance mathematical programming models, Wiens found exactly the opposite to hold true. Brink and McCarl discovered that while risk attitudes were important to farmers' cropping decisions, there was not a wide variation in risk attitudes among farmers in their study.

Also of concern is the fact that adding constraints to the objective function of L.P. models will not necessarily result in an efficient solution which incorporates farmers' concerns about risk. Instead, they may lead to the solution at a point on a less efficient function. This direct consequence of expanding the constraint set may mean that although the inclusion of multiple objectives under risk in farm planning models is intuitively appealing, this method may not give reliable results even if we determine the most appropriate decision rule from among the ones presented.

VII. CORRELATIONS BETWEEN RISK ATTITUDES AND SOCIOECONOMIC VARIABLES

In addition to deriving a numerical measure of attitudes toward risk, several researchers have made an effort to correlate risk coefficients with a variety of socioeconomic variables. The conflicting results which they obtain may be due to the different methods they used to derive risk coefficients, the fact that they consider quite different sets of socioeconomic varibles, and the different settings in which the research was conducted. This brief chapter presents their results with the purpose of finding areas of consistency.

The Findings

In their studies of Oregon grass seed farmers, Halter and Mason entered eleven farm and decision maker characteristics into a stepwise regression with risk attitude as the dependent variable. Three variables, percent of land owned, educational level, and age were used in a second stepwise regression which included the linear and quadratic terms of the variables as well as their linear interaction terms. The results of the final regression are shown in Table 7.1 along with the results obtained by Whittaker and Winter when they repeated the study in 1976.

Examination of Table 7.1 shows that the sign of every estimated coefficient changed between 1973 and 1976. It seems highly unlikely that the relationship between risk attitude coefficients and socioeconomic variables could have changed so much in only three years. To test the hypothesis that a change in income was responsible for the change in Pratt coefficients between the two studies, the change in the coefficient was regressed on the change in income. The R^2 was only .002 and the estimated coefficient was one-third the size of its standard error. Therefore, the change which is observed must have been related to a change in some socioeconomic variable which was not included in the model. Since neither set of authors include in their reports the eight socioeconomic variables which were rejected from the model on the basis of Halter and Mason's first stepwise regression, it is impossible to determine whether one, or a combination of these variables contributed to the results. A later study in the same region by Mason and Halter showed that acres of grass seed farmed was positively correlated to increases in risk aversion.

When Dillon and Scandizzo determined risk attitude coefficients of a group of small owners and sharecroppers in northeast Brazil, they found that the

TABLE 7.1

Estimated Coefficients and Standard Errors of Socio-Economic Variables Associated with Pratt's Absolute Risk Aversion Coefficients in Two Studies

Dependent Variable	A Education	B Age	C % of Acreage Owned	A^2	AxC	AxB	Constant	R^2
1973 Pratt Coefficient	-3.065 (2.393)	-.2304 (1.011)	1.566 (.0429)	-0.0449 (0.0143)	0.8631 (0.3278)	.0274 (.3085)	1.231 (6.961)	.413
1976 Pratt Coefficient	3.802 (1.081)	.5569 (.5468)	-.1257 (.0194)	.0380 (.00645)	-.8044 (.148)	-.1377 (.1394)	-4.329 (3.144)	.709

estimated coefficients were not normally distributed. This suggests that the socioeconomic characteristics of farm households, which were also not normally distributed, may account for some of the variation within each tenure group. Four socioeconomic variables for which data was readily available were used to test this hypothesis. These included the farmers age, income, household size, and ethical attitude towards betting. Utility free and utility function specific regression models were developed using a linear functional form to relate the risk premium requested by the i-th individual to the risk of the prospect presented to him in the experiment. The other variables in the model were socioeconomic variables and an additive random disturbance. The utility free model, which employed the risk premium as a monetary measure of risk attitude, was run twice, once without restrictions and once with a zero order restriction placed on the socioeconomic variables. A second set of models differed from the first in that the measure of risk used was the variance minus the squared certainty equivalent. In a quadratic utility framework, this is equal to the risk premium divided by the risk aversion coefficient. The set of regressions was run in unrestricted and restricted forms. The unrestricted equations provided marginal measures of risk aversion while the restricted forms provided average measures.

As in the case of the individual data, major differences exist between the values of the parameters' measures when subsistence (income required to maintain the farming unit intact) was and was not at risk. For sharecroppers, these differences extend to the entire estimated equation. For small owners, however, the estimated marginal risk aversion parameters under the two sets of circumstances are not significantly different. For both owners and sharecroppers, an increase in the riskiness of the random prospect induces an increase in the required risk premium. Increasing risk aversion was also found to be correlated with ethical beliefs against gambling, aging, and for owners, an increase in household size. In conformity with Arrow's hypothesis of declining absolute risk aversion with increasing wealth, increases in income were associated with a fall in the requested risk premium. For both tenure groups in both situations, larger risk premiums are required as risk increases.

Moscardi and de Janvry used three classes of variables to define the socioeconomic characteristics of the peasant households in their sample in Peubla, Mexico. The first class of variables was related to the nature of the household and included family size and age and years of schooling of the household head. The total amount of land under its control and the level of off-farm income were used to represent the income generating opportunities of the peasant household.

Only one variable was used to define access to public institutions, membership in a "solidarity group." These groups were created in conjunction with the Puebla Project to allow peasants access to credit not as individuals but as members of a group of five to twenty members.

Discriminant analysis was used to test the hypothesis that a systematic relationship exists between attitudes toward risk and the socioeconomic characteristics of peasant households. Eighty-four percent of the subjects were classified similarly by risk aversion coefficients and socioeconomic variables. It was found that higher degrees of risk aversion were positively correlated with age and negatively correlated with schooling, family size, off-farm income, land under control, and membership in a solidarity group. The results support the hypothesis that the risk bearing capacity of peasants can be explained in part by their socioeconomic characteristics. Particularly significant for that purpose are the extent of land under control, off-farm income, and membership in a solidarity group.

When Binswanger regressed eleven socioeconomic and structural characteristics on the partial risk aversion coefficients derived for peasants in rural India, he got some expected and some surprising results. To ensure that neither sex nor village membership affected the distributions, he first determined that estimated coefficients did not change significantly for males or females or across villages. One of the most surprising results of the regression analysis was the weakness of the relationship between physical assets, measured as the gross sales value of those assets, and risk aversion, especially given the strong effect that game size had on risk attitudes. The sign of the coefficient on wealth was consistently negative, but not always statistically significant. Wealth had little impact on behavior at the fifty rupee game level, an amount commensurate with monthly wage levels or small agricultural investments.

Higher levels of risk aversion were associated with low levels of education although the effect was not a strong one. When variables correlated with schooling, salary income and a progressive farmer dummy were suppressed, schooling had a much stronger effect. Past experiences with playing the gambles, or luck, was highly correlated with risk attitude, with success in prior games negatively correlated to increased risk aversion. The effects of "luck" did not wear off rapidly, but did tend to decrease as the stakes rose.

Increasing risk aversion was positively correlated with age at the half rupee and five rupee income levels but the two were negatively correlated at higher game levels. This result was unexpected as was the consistent result that risk aversion was not smaller for families with fewer dependents. As in the results published by Dillon and Scandizzo, tenants were shown to be less risk averse than landlords at low game levels. A negative correlation between risk aversion and transfers received supports the hypothesis that receiving income transfers reduces aversion to risk because the transfers provide insurance against adversity.

Binswanger concludes from these results that the difference in investment behavior observed among farmers facing similar technologies and risks cannot be explained primarily by inherent risk attitudes, but instead are induced by the existence of differing constraint sets.

As part of a study on risk efficient fertilizer application rates for farmers in Brazil, Crocomo regressed the socioeconomic variables of age, education, family size, tenure arrangement, income, size of farm, and contact with sources of information against risk aversion coefficients for 118 farmers. The only significant parameter was the information index, which was negatively correlated with increasing risk aversion. When a stepwise regression was run for all owners together, allowing for interaction terms, it was shown that increasing risk aversion was positively correlated with age, access to information, and an information-income interaction term. Increasing risk aversion was negatively correlated with increases in income, which supports Arrow's hypothesis of decreasing absolute risk aversion with increasing wealth. Discriminant analysis showed that over 85% of the individuals were classified similarly by risk aversion coefficients and socioeconomic variables.

Summary and Implications

A summary of the findings of the studies discussed in this chapter is presented in Table 7.2. It is important to note that the relationships found between socioeconomic factors and attitudes toward risk are not consistent across studies. This should not be surprising given the wide variety of methods used to generate the reported results and the differences in operational definitions of variables and environmental factors discussed in the summary of Chapter 5.

Nevertheless, the finding that local measures of attitudes toward risk are highly correlated with socioeconomic characteristics in developing countries indicates that there may be an important distinction between that part of risk taking behavior which is innate to the individual (not a consequence of economic variables or constraints) and that which is income or wealth determined. The innate propensity or desire or willingness to bear risk may be called

TABLE 7.2

Relationship Between Socioeconomic Factors and Increasing Risk Aversity

	Binswanger	Dillon and Scandizzo	Moscardi and de Janvry	Halter and Mason	Whittaker and Winter	Crocomo
Age	+,-[b]	+	+	+	-	+
Years of Schooling	ns		-	+	-	ns
Size of Family		+[c]	-			ns
Size of Land Holdings	-		-			
% of Holdings Owned	ns	+,-[d]	ns	-	+	
Off Farm Income	-		-			
Annual Income		-,+[e]				-
Solidarity Group Affiliation			-			
Luck[a]	-					
Ethical Belief Against Gambling		+				
Information Access						+

[a] Luck is determined by previous winnings in one-period money gambles.

[b] Risk aversion increased with age with low monetary gambles but decreased with age at higher levels of reward.

[c] Risk aversion increased with size of family for small owners but not for sharecroppers when subsistence was at risk.

[d] Results were highly dependent upon the functional form of the utility function used.

[ns] Tested but shown to be not statistically significant.

Blanks indicated factors not considered in the analysis.

preferential risk aversion while wealth or income's effect on the ability to bear risk may be termed induced risk aversion.

Huysam argues that when profitable technology exists, all farmers are eager to innovate. Therefore, preferential attitudes toward risk cannot account for differences in adoption. Rather, it is the degree of induced risk aversion which prevents small farmers from adopting new technology. The major policy implication that Huysam derives from this analysis is that removal of the disadvantages of small farmers requires institutional policies aimed at equalizing access to factor and product markets rather than some kind of intermediate low yielding technology. According to Huysam, underinvestment need not occur if agriculture is risky and farmers are risk averse. If farmers have effective mechanisms for self-insurance or risk diffusion, they may still invest up to the risk neutral optimum.

Berry echoes Huysam's position in arguing that unproductive or unprogressive behavior by small-scale farmers in developing countries is not the result of unusual aversion to risk but is the result of a limited capacity to bear risk. Berry further argues that since risk entails potential cost, risk bearing depends on access to resources with which to meet these costs, and there is no inherent inconsistency between risk aversion and profit maximization. Studies which take into account all of the costs of the farmer of alternative courses of action, including the cost of risk, often find that poor farmers' behavior is consistent with profit maximization.

According to Berry, when access to formal risk-spreading institutions is limited, participation in certain informal institutions or social networks is used to increase an individual's claim on resources. It thus becomes worthwhile for the individual to maintain or improve their position in that group through patterns seen by outsiders as wasteful. Market imperfections which limit the access of certain groups to risk spreading institutions cause apparent risk averse behavior. Therefore, policies which reduce uncertainty by increasing farmers' information about opportunities and constraints without simultaneously improving their access to resources will not increase their capacity to bear the possible consequences of risky events.

VIII. UNIVERSALITY OF UTILITY FUNCTIONS AND RISK ATTITUDE COEFFICIENTS

Information regarding individuals' attitudes toward risk is often elicited for use in current and future personal and policy decisions. This chapter examines evidence which raises questions regarding the reliability of utility functions and risk attitude coefficients derived using current practices. There is reasonable evidence that utility functions elicited from responses to hypothetical choices can be used to predict choices in other hypothetical situations. What has not been demonstrated is the ability to identify an actual choice set along with accurate subjective probabilities such that the expected utility hypothesis can be applied to actual choice conditions. There is also an increasing body of evidence which calls into question assumptions regarding the stability of preference over time, income, and situations, and our ability to rank individuals according to their derived risk attitude coefficients.

Applicability of Hypothesis Derived Utility Functions to Actual Choice Situations

Except in observed economic behavior studies, individuals' utility functions or risk attitude coefficients are determined within a contrived environment. The preferences exhibited within that environment may not accurately reflect the individuals' general preference. Masson and Roumasset have demonstrated that a utility function in one-period money, such as the gambling games used in directly elicited utility techniques, may be viewed as an indirect utility function of consumption consistent with short term borrowing and lending opportunities. As a result, an individual who is risk neutral with respect to their lifetime utility function may exhibit an apparently risk averse or risk preferring indirect utility function for one-period money because of capital market imperfections. Therefore, the attempt to separate attitudes from constraints may be impossible using one period gambles.

An empirical example can be seen in the Officer and Halter test of DEU techniques discussed in Chapter 4. The fodder reserve plans to which the predicted decisions were compared were substantially different in the first and second years. In the first year, actual fodder reserve programs were used as the standard for comparison, while in the second year, preferred fodder reserve plans were used. Lin, Dean, and Moore, in a test of the predictive ability of the expected utility hypothesis, showed that actual farm plans may not reflect true preferences because of factors which constrain the actual opportunity set of farmers so that they do not contain their utility maximizing choice. In fact, for none of the respondents was the actual farm plan in the individual's efficient set.

In a study in the same region as that used by Officer and Halter, Officer, Halter and Dillon found that measured risk aversion coefficients were not consistent with the levels of relative risk assumed by the adoption of specific managerial practices. For example, a farmer who was relatively more risk averse than another may select "less risky" stocking rates but "more risky" levels of fodder reserve than his counterpart.

The Impact of Changing Wealth Levels on Attitudes Towards Risk

The independence axiom, in conjunction with the other axioms of expected utility theory, implies that the individual's ranking of preferences corresponds to the expectation of a fixed utility function defined over final consequences of ultimate levels of wealth. Friedman and Savage, in estimating the utility function by fixing its endpoint values at two arbitrary wealth levels, indicate that the EUH would be violated if the use of another pair of wealth levels as reference points yielded a utility function differing in more than origin and unit of measure from the one initially obtained.

The procedure of integrating initial wealth with the outcomes of alternative gambles before expressing preference for any one gamble, referred to by Kahneman and Tversky as "asset integration," requires that when an individual is faced with alternative gambles expressed in terms of deviations from current wealth, he will choose the gamble whose distribution over ultimate wealth has the highest expected utility. Markowitz has noted, however, that the assumption that a utility function is defined over ultimate wealth levels is not consistent with the observed tendency of individuals of all wealth levels to purchase insurance and lottery tickets. He hypothesized that changes in wealth cause the utility function to shift horizontally so as to keep the inflection point in a Friedman-Savage utility function at or near the current or usual level of wealth.

Experimental evidence also suggests that individual gambling behavior at different initial wealth levels is more indicative of a shifting utility function than of movements along a fixed utility function. Davidson, Suppes, and Seigel found that even when participants' wealth levels had changed significantly during the period between experimental gambling situations they gave responses which were consistent with original game preferences, sometimes duplicating them exactly. Kahneman and Tversky have also concluded that the preference order of prospects is not greatly altered by variations in asset situations.

The Markowitz hypothesis of a shifting utility function implies that changes in initial wealth essentially cause the individual to go back and rerank the entire set of distributions over ultimate wealth levels. In the words of Eden, this hypothesis, which asserts that preferences cannot be defined independently of the current consumption point, is "disturbing to economists who use the assumption of 'constant tastes' quite heavily...it is hard to see how positive economics can do without this assumption and it is almost impossible to think of welfare economics without it."

Intertemporal Consistency of Utility Functions

Markowitz's hypothesis regarding the non-fixity of utility over ultimate wealth levels also raises disturbing questions regarding the intertemporal validity of an individual's utility function. The hypothesis implies that, regardless of current asset position, an individual would respond to a given gamble in exactly the same manner whenever it is presented to him. Empirical studies using farmers in Oregon and Michigan have shown that this is not the case. The results of studies conducted by Halter and Mason and Whittaker and Winter are discussed in Chapter 7.

Similarly, when Love and Robison repeated the study done by Carman using a sample of Michigan farmers, they found that risk attitude measures used to characterize utility functions using stochastic dominance with respect to a function had changed. When using discriminant analysis to classify farmers according to risk attitude, they found that the same variables (such as assets, income, or age) could not be used for all classes of decision makers within one time period, or for one class in both time periods.

These conflicting results lead to the conclusion that the Markowitz model may be applicable only in situations when assets are the primary factor influencing decision making. An example of this is an active investor in the stock market whose asset position can fluctuate dramatically in short periods of time and who immediately feels the impact of such fluctuations. But when dealing with farmers or other classes of decision makers whose assets are likely to remain stable over long periods of time, other factors may have a much larger influence on preferences and decision making behavior. For these decision makers, the hypothesis of asset integration may or may not hold; it is extremely difficult to validate the hypothesis. What is clear is that other factors influence preference rankings over time. In conclusion, Markowitz's hypothesis of non-integration of assets causing instability of preferences over ultimate wealth levels may be an appropriate model in some situations but does not necessarily imply intertemporal stability of preferences for gains and losses because of changes in other factors which may influence decision making behavior.

Group Utility Functions

Despite the questions raised regarding the intertemporal validity of hypothetically derived utility functions and their applicability to real world choice situations, farmers' risk attitude coefficients have been used in the development of extension programs. Because of the difficulties inherent in tailoring extension advice to idividual farmers on the basis of their attitudes toward risk, Officer, Halter and Dillon tested the feasibility of making fodder reserve program recommendations for Australian farmers on the basis of group utility functions. Assesssment of the errors between the group recommendations and the farmers' decisions (measured in terms of months of fodder reserve held) was used to determine the suitability of using a group utility function.

Predictions made using two methods of deriving the group's utility function: a utility function derived by taking the average of the group's individual utility functions, and a utility function obtained by taking the median utility function to represent the group as a whole. These were tested against the fodder reserve predictions made using individual utility functions and the criterion of cost minimization. Using individuals' utility functions, the average error in predicting months of fodder reserve held was only .26 months; the average error using a cost minimization criterion was .71 months. The method of using a median utility function to represent the groups utility resulted in an average error of .64 months of fodder reserve held. Predictions made using the average utility function had an average error of .86 months. Although the median measure of a group utility function was far less accurate in its prediction than the use of individual utility functions, it still seems that a risk-oriented group utility function approach can provide better recommendations than a more traditional approach such as expected cost minimization, which makes no allowance for risk.

Interpersonal Comparisons of Attitudes Towards Risk

The use of a utility function for making group decisions does not overcome problems of interpersonal comparisons of utility. Derived risk attitude coefficients are commonly used to rank individuals according to their degree of risk aversion. What is often overlooked is that a risk attitude coefficient such as the Arrow-Pratt absolute risk aversion coefficient is only a local measure of risk aversion. It does not necessarily follow that the same ranking of individuals will be obtained if a local measure is taken at any other point on their utility functions. Assume that there are two individuals, A and B, whose utility functions are shown in Figure 8.1. If the individuals' risk aversion coefficients are taken at Y_1, individual A will be more risk averse than individual B. When their risk aversion coefficients are taken at point Y_2, however, the ordering is reversed and individual B is more risk averse than A. Thus, the ranking of individuals by a local risk aversion measure is highly dependent upon where the measure has been taken. Pratt has shown that one decision maker can be said to be more risk averse than another if, and only if, his risk premium is always smaller than every other decision makers. Therefore, adequate rankings of individuals according to their attitude towards risk can only be made if we know their risk aversion in the large, over their entire utility function.

Summary

The major thrust of this chapter has been to reemphasize the point made in Chapter 5, that local measures of attitude towards risk cannot be generalized for use in global comparisons. Not only must concern be voiced over generalizations for distributions with dispersion beyond the local bounds, but also for the consistency of utility functions and risk attitude coefficients over changing levels of wealth and time. In light of the findings that utility functions and their associated risk attitude measure are very time, wealth level, and context specific, the usefulness of studies which attempt to precisely measure attitudes towards risk is diminished.

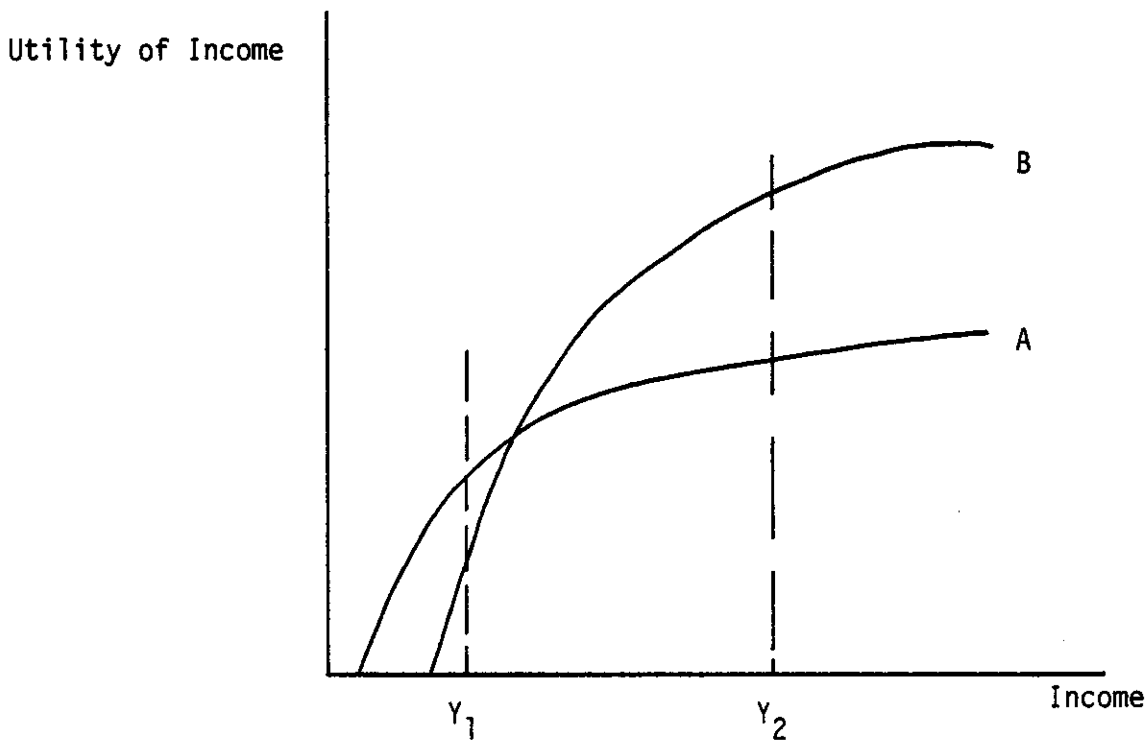

Figure 8.1. Ranking of Individuals According to Their Risk Attitude Coefficients

IX. CONCLUSION

The previous chapters have examined the strengths and weaknesses of the state of the art in decision theory and the measurement of attitudes towards risk in order to understand the implications which can justifiably be drawn from empirical studies in this area. This chapter summarizes conclusions regarding the adequacy of the tools used and the reliability of results obtained by these studies.

What Have We Learned?

Unfortunately, the most general conclusion that can be reached is that we still do not know much about the attitudes towards risk or chance taking held by farmers or the decision rules which they use in the face of uncertain or risky events. This is evidenced by the conflicting results obtained in many of the studies we have examined. It is difficult to ascertain whether the conflicting results are a result of actual differences between populations or other factors. The contributing factors may include differences in the methods used, operational definitions of critical variables, environmental factors which are not incorporated into the models, or simply poor data. Researchers with field experience are well aware of the many potential contributors to invalid data, especially in developing countries. It is impossible to evaluate even a carefully and adequately specified model with data that are invalid.

Despite this problem, several important points have come to the fore which can be useful in interpreting the existing literature and designing studies of one's own.

Local Measures of Attitudes Towards Risk

In Chapter 3 we reviewed many of the methods used to determine local measures of attitudes towards risk. Two important points became evident. One is that all of the methods described result in measurement of risk attitudes "in the small" and cannot be justifiably employed in inferring general conclusions about risk attitudes of a population or the ordering of individuals within the population according to general risk preference. This point was supported with specific evidence presented in other chapters which showed that we cannot expect that risk attitudes are constant over time, income, or situations. The second caveat is that all of the measures of "attitudes towards risk" are actually measures of the composite influences of attitudes towards risk or chance taking and the "pure" preference or utility for income in a riskless situation. It has also been shown that the functional form of the utility function used for the derivation of risk attitude measures will influence that measure.

In reviewing the methods used and conclusions reached in many applied studies which measure farmers' attitudes towards risk it was found that there is conflicting evidence about the distribution of risk attitudes within and between populations. Again, we cannot ascertain the source of these discrepancies. Especially puzzling are the conflicting results found by Halter and Mason and Whittaker and Winter who used exactly the same methods to measure risk attitudes of a single population at two different points in time. The most that we can conclude from these results is that either the methods employed are fundamentally flawed, or that risk attitudes do, in fact, change over time.

Risk Attitudes and Socioeconomic Variables

Farmers' attitudes towards risk are often determined for use in current and future personal and policy decisions. But, because there is evidence that risk attitudes are not stable over time and income levels, or across situations, repeated measurement of risk attitudes may be necessary. This is a costly and time consuming process. Therefore, attempts have been made to correlate risk attitudes with socioeconomic variables which are easily measured in the hope that, if the correlations are strong enough, farmers can be classified by risk attitude using these more visible proxy variables.

The relationships found between socioeconomic factors and attitudes towards risk were not consistent across studies. This may be due, in part, to the fact that each study considered a different set of socioeconomic variables. Another factor affecting the results may be that, as in the studies of risk attitude coefficients, different assumptions, operational definitions and methods were used in determining the population's risk attitudes. Nevertheless, the finding that local measures of attitudes towards risk are highly correlated with socioeconomic characteristics of farmers is a significant one.

One question which arises immediately is whether we can infer from the results that socioeconomic factors shape risk attitudes or whether there is just a statistical correlation between the two. Evidence that measured risk attitudes are different at different levels of income for the same individual may lead us to conclude that there is a causal effect. The nature of regression analysis and the conflicting results found by many of the studies should, however, lead us to be quite cautious in taking this approach.

The high levels of correlation between risk attitudes and socioeconomic variables may point to an important distinction which can be made between that part of risk taking behavior which is innate to the individual and that which is induced by income, wealth, or other socioeconomic factors. While little can be done about the aspect of risk taking behavior which is innate to the individual, policy measures may be able to directly influence that part which is induced by income, wealth, or other external factors.

Decision Rules for Farm Planning

Numerous studies reviewed in this report employ a selected decision rule to identify, predict, or prescribe an optimal farm plan for the decision maker. Although many of the decision rules were successful in meeting the criteria set forth by the researchers, there is no concrete evidence that any of them is the appropriate decision rule to be used in any one particular farm planning situation. This lack of evidence stems from the fact that very few of the decision rules were adequately tested in real world situations by comparing the predicted farm plan against the one preferred or actually used by the farmer. (Note that the actual farm plan is often not the preferred one because of the technical, institutional, or economic constraints present in the agricultural setting.) Furthermore, the fact that many different decision rules were deemed successful, and the lack of test results to the contrary, indicates that many different decision rules may have obtained the same result. Because of this, we cannot offer any conclusive support for a particular decision rule.

Because of the widespread use of linear programming models for farm planning purposes, special attention has been paid to linear programming models employing constraints in the objective function which are assumed to represent arguments other than profit maximization. Although these models are intuitively appealing because they combine a standard technique with the possibility of multiple objectives held by the farmer in the face of risky events, they all share one major drawback. The drawback is that the addition of multiple constraints to the objective function may well lead to the selection of a point from a less efficient EV set, rather than a new preferred point in the original set. None of the studies reviewed indicated the efficiency of the farm plan selected under various states of nature.

Although many of the linear programming models were successful in finding a solution which would maximize the constrained objective function, some, such as the model with constraints conforming to the minimax regret decision rule, did poorly both in ensuring that the maximum regret is as low as can be obtained and in satisfying farm income objectives.

Two of the most interesting results obtained in these studies were Low's finding that resource constraints and not different objectives or attitudes were responsible for different cropping patterns among farmers and Roumasset's study which also supports this hypothesis. These results, when combined with the hypothesized distinction between innate and induced attitudes towards risk, indicate an exciting area for future research.

Where Do We Go From Here?

We have found that although several models exist which provide useful theoretical frameworks for developing a conceptual understanding of decision making behavior under uncertainty, they fail to be adequate as complete explanations or predictors of farmer's attitudes towards risk or choices in the face of risky events for two reasons. First, none of the models have been empirically verified. Secondly, experimental evidence has shown that many of the tools used in the application of the theories to actual situations are deficient and may result in conflicting or misleading conclusions.

When looking towards future developments in the field of decision theory, one is struck by seemingly conflicting priorities. On one hand, there is a clear need for further development and testing of a model of decision making behavior and methods for its application which will yield accurate measures of risk attitudes and predictions. This requires overcoming many of the stumbling blocks cited in various points throughout this report. One of the greatest deficiencies is our lack of understanding of how subjective probability distributions are formed and then modified as learning takes place.

On the other hand, there is an immediate need, especially in the developing country context, for learning more about general atittudes towards risk and, perhaps more importantly, the determination of the factors which contribute to seemingly risk averse or risk loving behavior by agricultural producers. Answering these questions may not require the antecedent development of methods for accurately measuring attitudes towards risk. A more useful approach for these purposes may be to concentrate on the use of mathematical programming models. Of course, special attention must be given to specification of objective functions and constraints in the model, integrity of the data and the testing of models for efficiency and correspondence to real world behavior. An interdisciplinary approach utilizing the skills of economists, anthropologists, sociologists, and agricultural scientists is recommended for this task. An especially important focus for this type of research is the determination of the causes and the effects of innate and induced attitudes towards risk and the development of means to reduce the effect of constraints which induce risk averse behavior. In doing so we must broaden our focus to encompass all aspects of the decision process including problem definition, selection of the preferred action choice, execution of the decision, and acceptance of responsibility for the outcome which occurs. Although the importance of the entire decision process is often implicitly recognized, almost all of the recent research in decision theory focuses solely on the selection of the preferred action choice.

Despite the apparent conflict between these needs, research toward the development of an improved rigorous model of decision making under uncertainty and the development of a descriptive understanding of general risk attitudes and the factors which influence their development are, in fact, complementary. Disciplinary research on the development of better models and methods will allow for more accurate measurement of attitudes towards risk and increased predictive powers for individual decision makers and formation of appropriate policies in both the developed and developing economies. But this flow of useful information is not one way. Multidisciplinary reserach conducted to develop a descriptive understanding of general risk attitudes and the factors which influence their formation can provide useful knowledge to disciplinary researchers. Three specific areas are those of differentiating between innate and induced risk aversion, ascertaining decision makers' confidence in their probability estimates, and determining appropriate arguments to include in the utility function.

The lack of conclusive evidence to support the models and methods used to study decision making under uncertainty should not be interpreted as either a call to dismiss in their entirety the results of recent research or to abandon future studies. Instead, it is hoped that an awareness of the strengths and weaknesses of the state of the art in theory and methods will lead to the design of better studies and a closing of the gaps which exist in our understanding of decision making behavior under uncertainty.

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